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The Use of Personalised Driver Modelling to Investigate the Influence of Driving Style on Fuel Consumption

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Abstract

This thesis investigates the influence of different driving style on fuel consumption through the development of data-driven personalised driver models. A systematic study was conducted which consists of five main components, ranging from literature review to driver modelling and evaluation.

Two literature reviews are included in this thesis. The first review focuses on exploring the potential connections between driving style and fuel consumption, which confirms the motivation of this research. Meanwhile, the second review evaluates the existing studies on driver modelling that addressed human factors. The adopted modelling approach and feature parameters in this study are justified through the comparisons of existing studies in this second review.

Afterwards, a novel data-driven personalised driver modelling approach is presented, together with driving data collection, driving style classification and simulation evaluation. The major contributions of this thesis lay in six aspects. Firstly, a novel visual sensing algorithm is created to detect the potential leading vehicle and estimate the headway distance from the recorded dashcam footage. Secondly, a unique sensor fusion approach based on Kalman filter is developed to fuse the sensory data from radar and dashcam, and hence generate an optimised headway distance measurement. Thirdly, a novel driving style classification approach based on Support Vector Clustering is developed to differentiate the driving style variations. Fourthly, two fuzzy logic calibration approaches are adopted to infer the driver models from the collected data. Fifthly, the established driver models are incorporated into procedures anchored to the standard World-wide harmonized Light duty Test Cycle, to facilitate the investigations on the correlations between driving style and fuel consumption. Finally, a general process of developing personalised driver models is proposed to benefit relevant studies.

The conclusions reached are: (i) the proposed visual sensing algorithm can effectively estimate the headway distance from the recorded footages. (ii) The developed sensor fusion approach can compensate the drawback of each individual sensor with a strong robustness. (iii) The proposed driving style classification approach can differentiate driving style variations with a validated performance through the comparison with the jerk profiles of each participant. (iv) Both calibrated fuzzy driver models outperform the traditional PID-based model in characterizing human driving style. (v) In the proposed simulation scenario, the fuel reductions between the established aggressive and defensive driver models can be approximately 6% and 8% for each calibration approach.

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Publications

The presented work has led to the publication or peer review of a number of journal and conference articles. A list of these publications is provided below and references to these will be included as necessary within the chapters of this thesis.

Refereed journal articles:

1. Improved fuel consumption with technology aids to driving styles: a review

Y. Feng et al., Advance in Mechanical Engineering.

2. A Support Vector Clustering based Approach for Driving Style Classification

Y. Feng et al., International Journal of Machine Learning and Computing.

Peer reviewed journal articles:

3. Humanized driver modelling approach: a review

Y. Feng et al., Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering.

4. Driving style simulation with a fuzzy logic driver model calibrated using real driving data

Y. Feng et al., IEEE Transactions on Intelligent Transportation Systems.

Refereed conference articles:

5. Position estimation and autonomous control of a quad vehicle

Y. Feng et al., SAE Technical Paper, 2016-01-1878, 2016, doi: 10.4271/2016-01-1878.

6. Distance estimation by fusing radar and monocular camera with kalman filter

Y. Feng et al., SAE Technical Paper, 2017-01-1978, 2017, doi: 10.4271/2017-01-1978.

7. Driving style modelling with adaptive neuro-fuzzy inference system and real driving data

Y. Feng et al., 9th International Conference on Applied Human Factors and Ergonomics (Orlando, USA, 21 – 25 July 2018).

8. Driving style analysis by classifying real-world data with support vector clustering

Y. Feng et al., 3rd International Conference on Intelligent Transportation Engineering (Singapore, 3 – 5 September 2018).

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Abbreviations

ACC	Adaptive Cruise Control	K-NN	K-Nearest Neighbours
ADAS	Advanced Driver Assistance Systems	LKA	Lane Keeping Assistance
ANFIS	Adaptive Neuro Fuzzy Inference System	MDSI	Multidimensional Driving Style Inventory
ANN	Artificial Neural Network	MLIRL	Maximum Likelihood Inverse Reinforcement Learning
ARX	Autoregressive Exogenous	MPC	Model Predictive Control
B-BAC	Balance-Based Adaptive Controller	MST	Minimum Spanning Tree
CG	Complete Graph	NMPC	Nonlinear Model Predictive Controller
DBQ	Driving Behaviour Questionnaire	OBD	On-board Diagnostics
DD	Delaunay Diagram	PCA	Principal Component Analysis
DHG	Driving Habit Graph	PCMLP	Partly Connected Multilayered Perceptron
DIL	Decision Implementation Layer	PI	Proportional Integral
DML	Decision Making Layer	PID	Proportional Integral Derivative
DPM	Dirichlet Process Mixture Model	PI+GS	Proportional-Integral Gain Scheduling
DRM	Driving Relational Map	PMP	Pontryagin Minimum Principle
DSQ	Driving Style Questionnaire	PVRC	Powertrain and Vehicle Research Centre
DWT	Discrete Wavelet Transform	RAID	Redundant Arrays of Independent Disks
ECU	Engine Control Unit	RBF	Radial Basis Function
FOV	Field of View	R-CG	Reduced Complete Graph

FVD	Full Velocity Difference	RDE	Real Driving Emission
GMM	Gaussian Mixture Model	RMSE	Root Mean Square Error
GMR	Gaussian Mixture Regression	SVC	Support Vector Clustering
HCSM	Hierarchical Concurrent State Machines	SVM	Support Vector Machine
HMM	Hidden Markov Model	VW	Volkswagen
IPM	Inverse Perspective Mapping	WLTC	World-wide harmonized Light duty Test Cycle
IRL	Inverse Reinforcement Learning		

Chapter 1 – Introduction

The optimisation of driving style has drawn rapid growing research interest over the past two decades. It has been widely proven effective to reduce fuel consumption. However, the individual variations cannot be precisely determined owing to the unrepeatability nature of human behaviours. This thesis will investigate the impact of driving style on fuel consumption through reproducing human driving behaviours with personalised driver modelling.

The work presented in this thesis consists of five major components, namely real driving data collection, driving style classification, driver modelling, simulation validation and experiment verification. It is a comprehensive investigation towards personalised driver modelling. This work can potentially contribute to the incorporation of driving style variations in the standard drive cycle tests and the reproduction of RDE tests on chassis dynamometer. Moreover, it can also facilitate the development of personalised autonomous driving strategy in the near future.

This chapter firstly lays out the background for this project, and then present the associated aim and principle objectives. A brief description of each chapter in this thesis is also included.

1.1. Background

As a vital component of modern transportation, the automobile industry has witnessed a dramatic development over the past few decades. As shown in figure 1.1, the yearly number of cars sold worldwide has experienced a steady increase since 1990, and is expected to reach 81.6 million by the end of 2018 (Statista, 2018). With the estimated worldwide sum revenue to be $2,276.9 billion by 2018 (MarketLine, 2013), the blooming automobile industry has certainly boosted economic development and provided overwhelming convenience to the entire human society. While the benefits of automobiles are fascinating, it cannot be denied that the petroleum consumption is becoming much severer issues as side effects of this blooming industry.

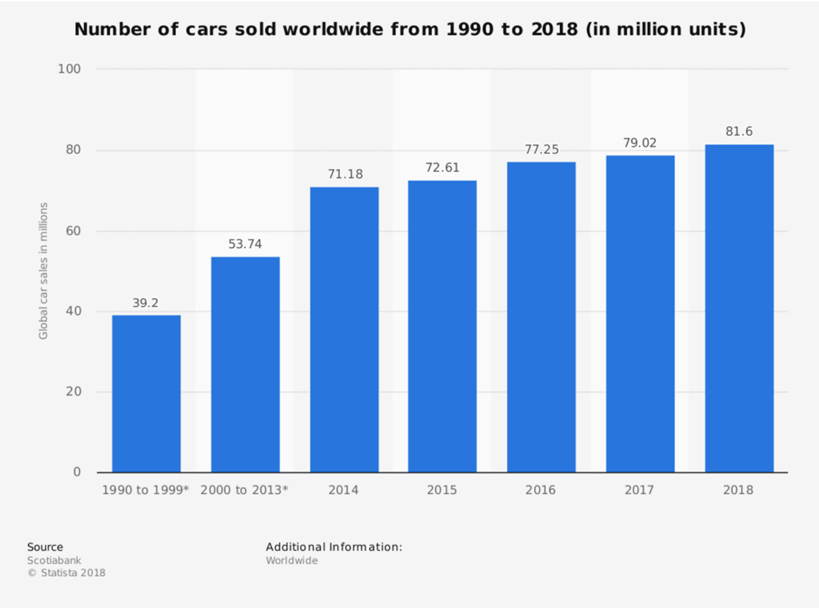


Figure 1.1. Statistics of car sold worldwide (Statista, 2018)

In order to mitigate the potential energy crisis, extensive efforts have been devoted to ease the increasing fuel consumption demand within the automobile industry, most notably, developing electric and hybrid vehicles. While these new types of automobiles can achieve reduced energy consumption (Howey et al., 2011), and have received unprecedented policy support (van der Steen et al., 2015), currently about 90 percent of vehicular fuel demands are still covered by petrol and diesel (Hill, 2012). Therefore, optimizing the fuel economy of conventional vehicles still has great significance. Several popular research trends are identified as, designing fuel-efficient engine (Bruce, 2014; Ingram, 2015), improving traffic flow (Toyota, n.d.; Pennoni, n.d.), and employing dynamic speed limits (Zegeye et al., 2009). Along with these technology advancements and macro control approaches, a growing research interest has also been witnessed in attempting to optimise driving style over the past two decades.

The concept of driving style, or vaguely referred to as driver behaviour occasionally, is first proposed by Elander et al. (1993). They defined this concept as “Driving style concerns the way individuals choose to drive, or driving habits that have become established over a period of years” (Elander et al., 1993). While there has not been a consensus on a unified definition of driving style (Deery, 1999; Saad, 2004; Lajunen and Özkan, 2011; Kleisen, 2011), it can be noted that driving style generally refers to the habitual way of driving, and has some distinct features between different categories (Sagberg et al., 2015). Extensive studies have been conducted to investigate this individual variation revealed during driving, with the majority focusing on the safety aspect. Nonetheless, the variations of fuel consumption caused by different driving styles have also been widely acknowledged for decades. Various eco-driving feedback mechanisms and training programmes have been developed to improve driving style, and hence reduce fuel consumption (Feng et al., n.d.).

While these approaches are proven effective, the individual variation of driving style still has not been precisely determined. This is mainly caused by the unrepeatable nature of human behaviours, making it unreliable to investigate driving style variations with human drivers. In order to more accurately quantify the influence of driving style on fuel consumption, this project proposes to develop personalised driver models to simulate different human driving styles. The high repeatability feature of driver models can be utilized to investigate the correlations between driving style and fuel consumption in a more controlled laboratory setting, which can produce more accurate and convincing comparison results.

Developing the proposed personalised driver model can benefit relevant research in various aspects. For instance, it can help to reveal the influence of driving style in procedures that are anchored to the standard drive cycle tests. Meanwhile, it can also facilitate the replication of RDE tests on chassis dynamometer, and the development of more economical and personalised ADAS and autonomous driving strategies.

1.2. Research question

This research work aims to investigate the influence of different driving style on fuel consumption by developing data-driven human driver style models. While the influence of driving style on fuel consumption has been widely recognised, the unrepeatable nature of human behaviour causes difficulty in quantifying the impact. Therefore, developing personalised driver models can approximate human driving styles and mitigate the unrepeatable nature issue, and hence facilitate the research on driving style and fuel consumption. Thus, this research proposes a process to facilitate the development of personalised driver models.

1.3. Aim and objectives

The overarching aim of this project is to investigate the influence of different driving styles on fuel consumption using personalised driver models. To fulfil this principal aim, four subsequent aims were derived as:

1. Collect sufficient real driving data using an instrumented vehicle.
2. Develop appropriate driver models that can represent different driving styles.
3. Investigate the correlation between different driver models and fuel consumption through simulation evaluation.
4. Develop a process that can calibrate personalised driver models.

Along with these four specified subsequent aims, the following eight primary objectives were identified for the proposed project.

- Review the existing literature on driving style and its correlation with fuel consumption.
- Review various approaches of driver modelling and associated feature parameter selection.
- Collect on road real driving data using an instrumented vehicle and perform post-processing to acquire demanded information.
- Classify different driving style using the driving data.
- Build driver models to represent different driving styles.
- Verify the performance of the established driver models.
- Investigate the correlations between driving styles and fuel consumption with the driver models.
- Develop the process to calibrate personalised driver models.

1.4. Contributions of the thesis

The major contributions of this thesis lay in six aspects. Firstly, in order to compensate the drawbacks of using an individual sensor, the monocular dashcam on the instrumented vehicle is hence employed to function as an additional source of headway measurements. Therefore, a video processing algorithm is created to detect the potential leading vehicle in each frame based on the rear light detection. Afterwards, the headway distance between both vehicles is estimated using the inverse perspective mapping algorithm.

With this additional source of headway distance measurements, the second contribution of this thesis is to develop a data fusion approach based on Kalman filter to fuse sensory measurements from radar and dashcam, and hence obtain an optimised headway distance estimation. This proposed sensor fusion technique can effectively compensate the drawbacks of each individual sensor and generate a more accurate and reliable measurement of headway distance. Afterwards, this optimised headway distance is synchronised with other vehicle-related parameters recorded by the data logger to form the dataset of the collected real driving data.

Thirdly, in order to differentiate different driving styles from the collected data, a novel SVC based driving style classification approach is developed. The proposed approach considers both the statistical and spectral features of the selected four parameters, namely headway distance, vehicle speed, engine speed, and pedal position. PCA is also implemented to identify the most prominent feature parameters, which are then feed into the SVC for driving style classification. Using this proposed approach, driving styles of three participants are classified. Moreover, the variations in each individual's driving style and the influence of external factors, such as weather condition and the driver's eagerness, are also investigated.

Afterwards, two different calibration approaches are employed to develop the fuzzy logic based driver model from the collected real driving data. The first calibration approach involves expert knowledge, while the second is more artificial and uses a neural network to infer the structure of the fuzzy controller. With the pre-classified driving data, driver models representing three different types of driving styles are obtained. The humanized performances of the established driver models are also evaluated through the comparison with a PID based model and the collected real driving data of corresponding human participants.

The fifth contribution of this thesis is to incorporate the established driver models into procedures that are anchored to the standard WLTC drive cycle test to investigate the correlations between driving style and fuel consumption. This proposed procedure simulates a car-following scenario, to allow the incorporation of driving style variations into the standard WLTC drive cycle test. A simulation environment was created in Simulink to evaluate the performance of the established driver models in this proposed procedure, and investigate the influence of different driving styles on fuel consumption.

The sixth contribution is the proposed process to develop personalised driver models. This process contains various aspects, ranging from personal driving data collection and driving style classification to personalised driver modelling. The proposed process provides a solution to infer personalised driver models from the collected driving data. The detailed procedure described in this thesis can benefit many relevant research areas, such as replicating RDE tests and incorporating more customization features into ADAS and autonomous driving strategy.

1.5. Thesis outline

Chapter 2 to Chapter 8 present the work according to each of the listed project objectives, respectively. The conclusions are summarised in Chapter 9. A brief overview of the contents of each chapter is given below.

Chapter 2 will first review the current knowledge of driving style, mainly focusing on its definition and classification. Afterwards, existing studies on improving driving style to reduce fuel consumption are introduced, to reveal their potential correlation.

Chapter 3 will first review the current adopted approaches for driver modelling to present the state-of-the-art of related research. Afterwards, a comparison will be given to demonstrate the advantages and drawbacks of each method. Finally, the feature parameters selected for driver modelling in each study will also be discussed to justify the parameter selection process of this project.

Chapter 4 will introduce the theoretical foundations of all the adopted methods and algorithms. This chapter has been divided into five parts, each explaining the real world data collection, driving data processing, driving style classification, driver modelling and calibration, and the established simulation environment, respectively.

Chapter 5 will present the results obtained from the real driving data collection. The performance of each individual sensor will be examined first. Afterwards, the correlation between both sensor measurements will be investigated. Finally, the optimisation performance of Kalman filter will be evaluated.

Chapter 6 will describe the driving style classification results of the collected driving data. The separate classification results will be presented first. Afterwards, a cross-comparison among these classified driving styles will be included. Finally, their correlation with fuel consumption and the influence of some external factors, such as weather and time of the day, are investigated.

Chapter 7 will evaluate the performance of the established driver model. The validity of the vehicle model will be examined first. Afterwards, the driver models developed using the two proposed methods are evaluated separately. A further comparison and discussion is also included.

Chapter 8 will summarize the results and key findings from this project. The identified future work that could benefit current research is also discussed.

Chapter 2 – *Review of research on driving style and fuel consumption*

This chapter first briefly reviews the current studies on driving style from both Psychology and Engineering background, with a major focus on its definition and classification approaches. Afterwards, technology aids developed to improve driving style and promote eco-driving are documented. These aids can be roughly divided into two groups as nationwide training programs and in-vehicle assistance tools. These identified studies are discussed to reveal the correlation between driving style and fuel consumption. The major findings from this chapter contain three aspects. Firstly, the concept of driving style is vague, as it lacks a unified definition. Secondly, while the classified driving style groups also vary significantly, some specific types (aggressive, normal, defensive) are commonly shared in identified studies. Finally, it is found that both training programs and assistance tools can effectively promote eco-driving. The first approach prevails in reaching more end-users, while the second approach is more cost-effective, and can maintain driving performance in longer terms.

The main content of this chapter has been submitted in the form of a review article to the Advances in Mechanical Engineering.

2.1 Introduction

Historically, research on driving style was mainly conducted by psychologists, with the primary focus of driving safety (Sagberg et al., 2015). According to Shinar (2007), these studies used the concept of “accident proneness” and investigated the individual variations on the probability of crash involvement. The earliest research of this type was implemented by Tillmann & Hobbs (1949). They interviewed a group of drivers from a taxi company and found significant difference in personality and background between high and low accident drivers. The famous saying “A man drives as he lives.” was also proposed in this research. Their findings confirmed the hypothesis that driving style can be affected by personal factors. Afterwards, extensive research was conducted to investigate the correlation between driving style and safety (West et al., 1993; French et al., 1993; Deffenbacher et al., 1994; de Winter and Dodou, 2010; Amado et al., 2013).

Unlike psychology research, which has a history of over six decades, driving style study is still a relatively new topic among engineering researchers, with a major focus on reducing fuel consumption. The majority of such research was conducted within the last two decades. Meanwhile, it should be noted that while the research term “driving style” is used in both subjects, they are referring to different concepts in most studies. In Psychology research, driving style, or occasionally referred to as driving behaviour, contains all aspects of driver’s act during the driving. It is not merely about the pattern of driving, but also includes information that is not directly linked with driving manoeuvre, like driver’s eye movement, facial expression and even heart rate. While in engineering research, driving style tends to refer to its literal meaning, the pattern of driving, which mainly consists of the preference of car-following behaviours, mode of acceleration and deceleration, and gear shifting strategies. This coincides with the different research focus of both subjects. While engineers focus more on vehicle state to reduce fuel consumption, psychologists concern more on driver’s monitor to detect safety critical events. With a primary focus of investigating the correlation between driving style and fuel consumption, the conception of engineering is hence adopted in this thesis.

2.2 Driving style definition

Although the first research focusing on individual driving difference was conducted in 1949 (Tillmann and Hobbs, 1949), the conception of driving style was not clearly defined until 1993 (Elander et al., 1993). According to Elander et al. (1993), it was defined as “Driving style concerns the way individuals choose to drive, or driving habits that have become established over a period of years”. Meanwhile, other researchers proposed different definitions of this concept, as shown in table 2.1.

It can be noted from table 2.1 that different researchers’ definitions of driving style vary significantly. These definitions can be roughly divided into three groups. In the first group, driving style mainly refers to the habitual dynamic control of the vehicle on the road, which can be regarded as the direct reveal of the difference (Deery, 1999; Saad, 2004; Murphey et al., 2009; Berry, 2010; Lajunen and Özkan, 2011; Kleisen, 2011). Meanwhile, the second group focuses more on the inner cause of the variations of driving style, and considers the personal attitude and experience of the driver (Rafael et al., 2006; Ishibashi et al., 2007; de Groot et al., 2012). As proposed by Chung and Wong (2010), the third group is a combination of both, which contains both the direct reveal (headway and speed) and personal factor (attentiveness and assertiveness). While these personal factors are the inner cause of different driving styles, they can only be vaguely measured using questionnaires. Therefore, the first group of definitions is more favoured in this thesis. Although the definitions vary with these researchers, the essences share many common features. Therefore, it can be summarized that driving style refers to the driver’s own habitual choice of driving manoeuvre. Moreover, it should be noted that only two studies were conducted before 2005 (Deery, 1999; Saad, 2004), all others were published afterwards. This phenomenon also confirms the growing research interest in this area.

Table 2.1. Driving style definitions

Author	Year	Definition
Berry	2010	Driving style refers to the level of driving aggressiveness and includes the effects of the vehicle, driver, and driving environment. Driving style can be thought of as the accumulated velocities and accelerations used during a specific type or mode of driving.
Lajunen & Özkan	2011	Driving style concerns individual driving habits-that is, the way of a driver choose to drive.
Deery	1999	Driving style is concerned with decision making aspects of driving, that is, the manner in which people choose to drive or driving habits that have developed over time.
Kleisen	2011	One’s preferred way of driving that, over time, develops into driving habits.
Saad	2004	Driving style is described as a relatively stable characteristic of the driver, which typifies his/her personal way of driving, the way he/she chooses to drive.
Murphey *et al.*	2009	Dynamic behaviour of a driver on the road.
Ishibashi *et al.*	2007	An attitude, orientation and a way of thinking for daily driving.
Rafael *et al.*	2006	Driving style is defined as a set of activities and steps that an operator uses when driving an engine powered vehicle, according to his personal judgment, experience and skills.
de Groot *et al.*	2012	Driving style is the way in which a driver chooses to driver and is governed by a combination of social, neurobehavioral, and biological mechanisms.
Chung & Wong	2010	The ways drivers choose to drive or habitually drive. This includes choice of driving speed, headway, and habitual level of general attentiveness and assertiveness.

2.3 Driving style classification

Similar with the proposed definition of driving style, no consensus has been reached on a unified classification of this concept either. In early studies, driving style was not clearly classified into several distinct groups. The variations of driving style was mainly evaluated by level of aggressivity or violation using different questionnaires (Sagberg et al., 2015). For example, in the earliest DBQ by Reason et al. (1990), it has item like “Drive especially close or ‘flash’ the car in front as a signal for that driver to go faster or get out of your way.” to indicate driving aggressivity.

While in DSQ and MDSI, different dimensions of driving style were isolated and used to represent distinct driving style. The classified driving style groups vary in following research. Table 2.2 shows 15 identified research. It can be noted that although driving style is classified and labelled differently in these studies, they share some similar components, such as aggressive, normal and economical.

Table 2.2. Driving style classifications

Authors	Driving style				
Lee & Öberg	Aggressive	Normal	Calm		
Fonseca et al.	Aggressive	Normal	Mild		
Rui and Lukic	Aggressive	Normal	Mild		
Zorrofi et al.	Aggressive	Normal	Mild		
Stoichov	Sporty	Medium	Calm/Economical		
Tricot et al.	Sporting	Medium	Economical		
Dorr et al.	Sporty	Normal	Comfortable		
Sagberg et al.	Aggressive	Deviant/Risky	Defensive	Concentrated/ Focused	
Murphey et al.	Aggressive	Normal	Calm	No speed	
Chung & Wong	Angry/ Hostile	Reckless	Anxious	Patient/Careful	
Gense	Sporty	Defensive	Egg style	New style	
Aljaafreh et al.	Very aggressive	Aggressive	Below normal	Normal	
Meiring & Myburgh	Aggressive	Inattentive	Drunk	Normal/Safe	
Taubman-Ben-Ari et al.	Angry	High-velocity	Risky	Anxious	
	Dissociative	Patient	Careful	Distress-reduction	
Bär et al.	Aggressive	Anxious	Economical	Keen	Sedate

2.3.1 Typical driving style

Aggressive driving style, or sporty, hostile and angry driving style, is the behavioural pattern consisting of risky speeding, abrupt speed change, harsh acceleration and deceleration, and improper lateral position maintenance (Meiring and Myburgh, 2015). Although labelled differently, all mentioned research in table 2.2 identified this driving style. Meanwhile, there are also some other research only focus on aggressive and normal driving style (Macadam et al., 1998; Berry, 2010; Johnson and Trivedi, 2011; Stichter, 2012). Aggressive driving style is probably the most extensively explored driving style in previous studies. This is because aggressive driving style represents the most dangerous behaviour and it increases fuel consumption and exhaust emissions as well. It deviates from the norm and expected behaviour of a driver and is a main cause to deadly crashes (Johnson and Trivedi, 2011; Zhao et al., 2013).

Normal driving style, or medium, typical and safe driving style, is the reference for isolating other driving styles. It is used as the baseline for classification. Although the definition of normal driving style may vary greatly between different research, it refers to the driving style that is most commonly witnessed, and neither too aggressive or too defensive.

Economical or eco-driving is a relatively newly identified and promising driving style and is developed since the mid-90s (Alessandrini et al., 2012). It is proposed after identifying the influence of driving style on fuel consumption and exhaust emissions. The potential fuel reduction between economical and aggressive driving style is estimated to be 10%-15% in reality (Vermeulen, 2006; CIECA, 2007; Alessandrini et al., 2012). Meanwhile, Zorrofi et al. (2009) suggested a fuel saving of 60% through their simulated hybrid transit bus model. Major research on eco-driving is conducted within European, while other countries are also shown awareness of this potential benefits in last decade (Business wire, 2009; Symmons et al., 2009). Some general principles are summarized to denote economical driving style (Haworth and Symmons, 2001; Eco-driving, 2011), which are

- Shift to higher gear at approximately 2,000 RPM

- Driving to match the traffic rhythm
- Skip gears when it is appropriate
- Maintain a steady speed at low RPM
- Keep engine idling to a minimum

Many websites have been established to popularize this beneficial driving style (Business wire, 2009; Symmons et al., 2009; Eco-driving, 2011). Meanwhile, driver training programs and on-board driving assistance tools have also been developed to promote this driving style.

Along with these three most common driving styles, research listed in table 2.2 also has some particular driving styles, such as risky, inattention, drunk and defensive. While risky driving and aggressive driving are highly correlated, the major difference is hostility, as risky driver mainly wants to seek speeding sensation instead of being hostile. It is first identified by Taubman-Ben-Ari et al. (2004), and has also been used in some following research (Dula and Ballard, 2003; Richer and Bergeron, 2009). Some typical items of risky driving are identified as, “enjoy the sensation of driving on the limit”, “like to take risks while driving”, and “fix my hair/makeup while driving” (Taubman-Ben-Ari et al., 2004).

Meanwhile, inattention driving can be described as an instantaneous deviation from normal driving behaviour followed by sudden correcting reactions (Meiring and Myburgh, 2015). Driver inattention is classified into four groups by Neale et al., which are secondary task engagement, fatigue, driving related inattention to the forward roadway, and non-specific eye glance (Neale et al., 2005). It is a major cause of accidents, resulting in 3092 people killed and 416,000 injured in 2010 in USA alone (Bergasa et al., 2014).

Drunk driving may include features of both aggressive driving and inattention driving. However, it is mainly caused by degenerative influence of alcohol instead of driver’s intention. A drunk driver tends to be over confident and may have reduction in self-discipline and concentration, leading to risky and dangerous driving behaviour (Abdel-Aty and Abdelwahab, 2000). Typical drunk driving usually contains speeding, harsh acceleration and deceleration, poor lateral control and misjudgement of traffic. According to the Department of Transport of UK, 280 people were killed in drunk driving accidents in 2012, which accounted for 16% of all road deaths (Department for Transport, 2013). Due to the high correlation with severe accidents, drunk driving is forbidden in most countries.

Unlike those negative driving styles, defensive driving is often conceptualised as the contrary to aggressive driving (Sagberg et al., 2015). While it has not been specifically defined, defensive driving generally refers to moderate acceleration/deceleration, properly maintained headway distance and careful participation in traffic flow. It has a high correlation with normal driving but in a more passive manner. In the research conducted by Tzirakis et al. (2007), they found aggressive driving could increase fuel consumption up to 137.3% for petrol vehicles and 128.3% for diesel vehicles when compared with defensive driving.

2.3.2 Driving style classification method

Along with the differences on classification of driving style, the adopted classification methods also vary with different researchers. In the review by Meiring and Myburgh (2015), they identified several artificial intelligence algorithms for driving style analysis. Among these algorithms, Artificial Neural Networks (ANNs), clustering techniques and Fuzzy Logic have been previously used for driving style classification. For instance, Aljaafreh et al. (2012), Al-Din et al. (2013), and Dörr et al. (2014) developed fuzzy logic based classifiers. Meanwhile, Macadam et al. (1998) and Meseguer et al. (2013) used Neural Network to differentiate driving styles. Moreover, other methods, such as K-means and hierarchical clustering (Constantinescu et al., 2010), K-nearest neighbours (Vaitkus et al., 2014), and self-organising map (Albers and Albrecht, 2005) have also been applied for driving style classification.

Along with these artificial intelligence algorithms, there have also been some other methods previously adopted to classify driving style. As most driving styles are closely related with acceleration/deceleration behaviour, these methods directly classify driving style based on measurements and derivatives from acceleration profile. An early research was conducted by Langari and Won (2005). They used the ratio of the standard deviation of acceleration and the mean acceleration to classify driving styles into aggressive, normal and calm (Langari and Won, 2005; Won and Langari, 2005). Meanwhile, Murphey et al. (2009) used jerk (the rate of change in acceleration/deceleration) to classify the same driving styles, and found their method outperformed the previous one. Moreover, Qi et al. (2015) adopted a data mining technique to classify driving style. Their proposed approach is an ensemble clustering method based on the kernel fuzzy C-means algorithm and the modified latent Dirichlet allocation model. They focused on longitudinal driving behaviour and derived three driving styles, which are aggressive, moderate and cautious. Unlike most previous research, drivers were not classified into distinct groups, and were allowed to have a combination of these styles.

2.3.3 Summary

While these studies have successfully classified driving styles into several groups using real driving data, a major concern is the parameters they used for classification are not well justified. Most of the studies selected acceleration and jerk for the classification. While these parameters can indicate driving style variations, it should be noted that other parameters, such as the following distance to the leading vehicle, could also be crucial to the classification results. For example, if the leading vehicle suddenly stops, a harsh brake can indicate a defensive driving style rather than aggressive. Thus, it would be beneficial to collect more driving related data, and apply feature extraction approach to isolate influential parameters prior to classifying driving styles. Although this will require more sensors to record traffic scenarios, it can produce more accurate and convincing classifications. Meanwhile, most of existing studies classify drivers using the entire trip data. While this is suitable for these studies, a more plausible approach is to divide the trip into several segments. This is because the driving style of a driver can vary during the trip. Even an extreme aggressive driver will not maintain aggressive driving throughout the entire trip, and can drive defensively in some occasions. Therefore, a sliding window based method may be more appropriate. The entire trip can be divided into several segments according to revealed driving style, and the driver can be evaluated as a mixture of several driving styles, indicated by percentages.

Although classifications of driving style vary with different researchers, the influence of driving style on fuel consumption is widely acknowledged and investigated. Negative driving styles, such as aggressive driving and risky driving, can lead to higher fuel consumption, while economical driving can efficiently reduce unnecessary consumed fuel. Therefore, extensive research efforts have been devoted to promoting eco-driving style in recent years. Based on the adopted methodology, these studies can roughly be divided into two groups, which are driving style training programs and in-vehicle assistance tools.

2.4 Driving style training programs

2.4.1 Nationwide training programs

As indicated by Ho et al. (2015), driving style training programs mainly focus on promoting eco-driving style, with the first application occurred in 2001 in Europe. Afterwards, several eco-driving projects and campaigns have been conducted within Europe. Meanwhile, Eco-driving has also been incorporated into driving lessons across Europe under the EU regulations (Barkenbus, 2010). Major eco-driving promotion programs within Europe are identified as ECODRIVEN (2009), ECOWILL (2011), and ecoDriver (Carsten et al., 2016). ECODRIVEN (European Campaign On improving DRIVing behaviour, ENergy-efficiency and traffic safety) is supported by the European Commission Energy Efficiency programme Intelligent Energy Europe (IEE), aiming to optimise end users' driving behaviour by regularly presenting eco-driving activities (EcoDriven, 2009). This campaign involves nine EU countries, which are United Kingdom, France, Netherlands, Belgium, Finland, Austria, Poland, the Czech Republic and Greece. It had reached over 20 million licensed drivers during its operation period from January 2006 to December 2008. Although the focus of this campaign was to reduce exhaust emissions, it reduced approximately 10% fuel consumption in the long term (EcoDriven, 2008). The detailed fuel saving within the campaign is shown in table 2.3.

Table 2.3. Fuel savings in ECODRIVEN

Country	Participants	Fuel saving description
UK	494	22.5% average reduction; 16.8% on public roads
Germany	765	20.7% short term reduction; 10% long term reduction
Finland	101	14% average reduction
Austria	1700	10.5% average reduction

Moreover, IEE also hosted a subsequent project, which is called ECOWILL (ECO driving-Widespread Implementation for Learner Drivers and Licensed Drivers). It focuses on promoting short duration eco-driving training programs for both learners and licensed drivers (EcoWill, 2011). This project was launched in May 2010, aiming to reduce carbon emissions by up to 8 million tonnes in 5 years. It involves 13 European countries, which are Austria, Croatia, Czech Republic, Finland, Germany, Greece, Hungary, Italy, Lithuania, Poland, Spain, Netherlands and United Kingdom. ECOWILL engaged administrations and driving schools to incorporate Eco-driving in both driving tests and driving lessons through collaboration with EFA (driving school association) and CIECA (examination association). Eco-driving elements were introduced into learner drivers' training, both theoretically and practically. Virtual training software was also developed to reach more end-users. Five golden rules and eight silver rules were summarized as a general guidance of eco-driving.

Meanwhile, ecoDriver was a more research-oriented project that funded by the European Union Seventh Framework Programme (Carsten et al., 2016). It operated from October 2011 to March 2016, and consisted of 12 partners from eight EU countries, which are United Kingdom, France, Italy, Netherlands, Belgium, Germany, Sweden and Spain. This project aimed to optimise feedback system and hence improve the acceptance and compliance of green driving advice. An average energy saving of 4.2% was achieved in the real-world trials of the developed six ecoDriver systems, ranging from an Android app to complete device and vehicle manufacturer designs. Unlike ECODRIVEN and ECOWILL, the major focus of this project was in academia and industry, and its findings were mainly presented in relevant conferences. Nevertheless, according to Carsten et al. (2016), ecoDriver’s website had attracted rapidly increasing visitors (777 visitors per month in the first three months of 2016).

Along with Europe, eco-driving programs have also been conducted in other countries. In Singapore, Volkswagen hosted an eco-driving program named Think Blue (Ho et al., 2015). It was launched in 2011, aiming to teach drivers to reduce fuel consumption and exhaust emissions without compromising speed and time. Each eco-driving session consists of three stages, a prior-lesson drive cycle, a classroom training session and an after-lesson drive cycle. Ho et al. (2015) analysed obtained data from 116 participants and found the average short-term fuel reduction is approximately 16%. Although the long-term effect was not monitored, they suggested a potential 2-10% fuel saving based on previous studies. Meanwhile, Japanese government has also started to promote eco-driving since 2003. A committee named EcoDriving Promotion Liaison JAPAN was formed to popularize eco-driving to public. This committee proposed 10 general suggestions of eco-driving in 2003 and designated November as “Eco-Drive Promotion Month” since 2010 (Luther and Baas, 2011). While in New Zealand, ecodriver is the only company specialising in eco-driving training courses (Ecodriver, 2014). This company operate in the same manner as driving instructor. They provide one on one fuel-saving course. Each course lasts 1.75 hours, consisting of 30 minutes theory session, 60 minutes driving session and 15 minutes summary session. These programs share a similar procedure, which is developing eco-driving rules, hosting popularization activities and conducting on road training sessions.

While these programs can effectively arise public awareness of eco-driving and reach more end-users, they are expensive to conduct and difficult to measure the long-term effect. Moreover, the training time for each trainee is relatively short, usually less than three hours. The lack of repetitive training can also cause a decreasing performance among trainees in long term.

2.4.2 Driving simulator based training programs

Apart from those macro eco-driving promotion programs, there is another type of training programs, which uses driving simulators to popularize eco-driving. According to Robin et al. (2005), the benefits of simulator trainings can be identified as, safe driving environment; repeatable driving scenarios; high quality measurements of driver performance and resist to weather conditions. However, this type of programs can only reach a smaller group of drivers due to the limited availability of the simulators. Thus, these programs usually target at specific types of drivers, such as truck drivers and taxi drivers.

The complexities of driving simulators vary with different research. It can be a simple desktop PC, equipped with a steering wheel and pedals, or can be a complex device with six or more degrees of freedom. Some research also includes partial or complete real vehicle to enhance the sense of realness. Driving simulators were mainly used for training learner drivers and investigating specific driver behaviours (Azzi et al., 2010). Owing to the increasing similarity with real driving, some researchers have started to use driving simulator to promote eco-driving recently.

Within a French government funded project, geDRIVER, Renault used the premium driving simulators developed by Oktal to investigate the efficiency of eco-driving trainings (Beloufa et al., 2012). As shown in figure 2.1, this simulator consists of three screens and uses dashboard and driver's compartment from real vehicles to increase realness. Although this simulator can be equipped with motion system, the static version was adopted for the research. An interactive guidance system with visual, audio and tactile feedbacks was also developed. They assessed the influence of six eco-driving rules with 72 participants. Although the fuel reduction was not measured, they recorded a 7% CO_2 reduction after lessons and a further 3% reduction by adopting the guidance system. While this simulator has a rather simple configuration, an important contribution of this study is the assessment of eco-driving rules, of which they found rules associating with anticipation and deceleration strategy have a more evident influence. This could be more beneficial if associated with the additional workload perceived by drivers, which can hence help to rank the eco-driving rules.

Figure 2.1. Oktal driving simulator (Beloufa et al., 2012)

To further increase the simulation realness, Zhao et al. (2015) incorporated a complete vehicle in their driving simulator. Their driving simulator is fixed-base and consists of three screens providing 130° field of view, as shown in figure 2.2. This simulator incorporates an eco-driving feedback system that can provide visual and audio feedbacks. Meanwhile, as an additional feature, it can also provide general and specific driving advices after each test run, which can be regarded as static feedback. The validation experiment of this simulator involved 22 divers, 10 professionals and 12 non-professionals. They measured a fuel saving of 3.43% with solely the static feedback, and 5.45% with dynamic feedback. They also found a difference between professional and non-professional drivers. While dynamic feedback led to a better fuel saving in both groups, static feedback system performed better with professional drivers, resulting in an average of 0.76% more fuel saving compared with non-professional drivers. Meanwhile, non-professional drivers benefited more from dynamic feedback, with 0.62% more fuel saved. This could be partially because professional drivers are more familiar with driving, and hence feel less difficult to apply static advices in their driving. Meanwhile, non-professional drivers tend to be more inconsistent with their driving, and can adapt faster to dynamic feedbacks. A unique contribution of this study is the comparison between professional and non-professional drivers. Based on their findings, it can be implied that differentiating professional and non-professional drivers might be more beneficial when developing such eco-driving promotion systems. Meanwhile, more following studies are recommended to investigate the on-road performance of this difference. Assuming this difference is consistent, it should hence be worthy to develop specific eco-driving systems for professional drivers, to differentiate them from others.

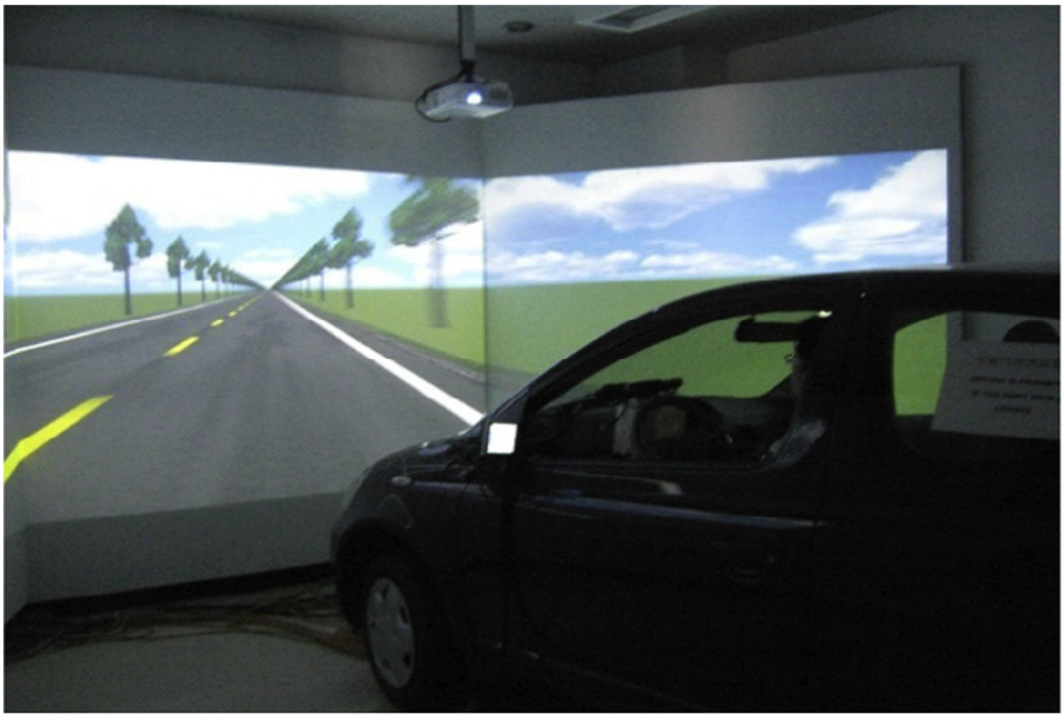


Figure 2.2. Driving simulator by Zhao et al. (2015)

Figure 2.3. Driving simulator by Hiraoka et al. (2009)

Another similar research was conducted by Hiraoka et al. (2009). Their simulator consists of three screens and can display instantaneous and average fuel economy as visual feedback, as illustrated in figure 2.3. Unlike previous studies, their research focused on the car-following scenarios. They also compared the difference of eco-driving advices between Japan and Germany, gentle acceleration and slightly faster acceleration respectively. Twelve participants were requested to follow a simulated leading vehicle. The fuel consumed during normal driving, driving with visual feedback, and driving according to eco advices were recorded. They found that even without instructions about eco-driving, fuel economy was increased by 9.9% with the on board visual feedback. Meanwhile, following Japanese and German eco-driving advices improved fuel savings to 15.4% and 14.5% respectively, which means gentle acceleration can generally save more fuel. However, Japanese eco-driving advices tend to lengthen the headway distance and hence have a larger likelihood to cause traffic congestion. Therefore, it is still difficult to judge which advices prevail. Moreover, it is worthy to note that static instruction saved more fuel than dynamic visual feedback in this research, while others found dynamic feedback can always further reduce fuel consumption (Beloufa et al., 2012; Zhao et al., 2015). This may be partially caused by the test order. In contrary to other experiments, participants drove with dynamic feedback prior to receiving any eco-driving instructions in this research. Therefore, it can be summarized that although dynamic feedback system may have less impact on optimizing fuel economy than static instructions separately, a better fuel economy can be achieved by combining them together.

While the simulators in these mentioned studies are effective in promoting eco-driving, they are static and lack of simulating road interactions. In order to maximize the similarity to on-road driving, the European Aeronautics Defence and Space developed a Full Mission Simulator in 2003, which is also the UK's first Truck Driving Training Simulator (Reed, 2010). Instead of using multiple monitors and vehicle body, this simulator is based on a Mercedes Actros cabin, with six degrees of freedom. This simulator can provide a 270° field of view with seven projectors, and the driver is completely isolated in it. It can perform pitch, roll, heave, yaw, surge and sway to maximize the similarity to real driving. Figure 2.4 shows the general structure of the simulator.

In its first commercial application of eco-driving training, six truck drivers from Allied Bakeries visited TRL twice to participate the training, with a two months gap. An average fuel saving of 7.3% was recorded in real world driving as the consequence of the training. 250 tonnes CO_2 reduction would also be achieved annually with the improved driving style. Meanwhile, the long-term effect of the training was recorded on one driver, who remained on the same route with the same type of vehicle. His fuel efficiency improved 15% right after the training, and it gradually reduced and remained at 7% over a year. Therefore, the training was still proved effective even with the decreased long-term improvement. While this simulator is more expensive, it can provide a high-level sense of realness. Therefore, the participants can behave more naturally, and it would be easier for them to transfer the eco-driving style to real world. Meanwhile, the commercialized applications with other companies also indicate the interest in eco-driving from public, especially fleet managers. Moreover, these commercial collaborations can also help to cover partially the cost of developing such simulators, which could benefit TRL in return.

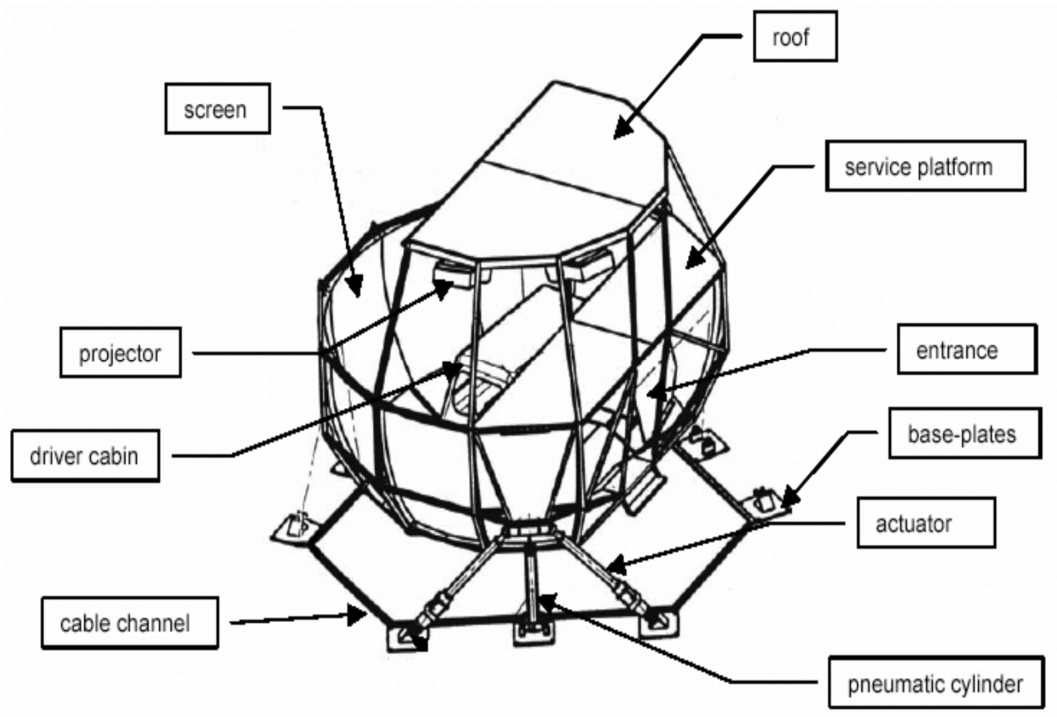


Figure 2.4. Driving simulator in TRL (Reed, 2010)

Meanwhile, Sullman et al. (2015) also conducted a similar research for bus drivers. Their simulator is a Volvo bus body mounted on an electro-pneumatic motion platform that can perform 4 directions of movements. 3 screens and 4 projectors are used to provide a 220° field of view to the driver. The structure of this simulator is shown in figure 2.5. This research assessed the performance of eco-driving simulator training on bus drivers, and the transferability to real world. During their simulator experiment, 47 bus drivers were divided into two groups, with 29 drivers in treatment group and 18 in control group. Both groups first completed a normal drive as comparison basis. Afterwards, five eco-driving rules were taught to the treatment group, while the control group received first aid training. All drivers were then requested to complete the test drive again. While the fuel economy of the control group almost remained the same, a significant improvement was recorded within the treatment group. Moreover, the transferability to real world was also assessed. An average of 11.6% fuel reduction was achieved right after the training, and a further reduction to 16.9% was recorded six months after the training. One unique contribution of this study is the incorporation of the control group. It can help to eliminate some disturbances that may also increase fuel economy, such as habituation, adaptation to the simulator and fatigue, and hence validate a more convincing training effect. Moreover, it also assesses the transferability to real world, and the positive correlation between simulator and real world confirms the validity of these simulator studies. However, it should be noted that the further reduction in the long-term experiment is in contrary to other research (af Wåhlberg, 2002; af Wåhlberg, 2007; Beusen et al., 2009; Reed, 2010) and the common belief that training effect will gradually decrease to a lower level. This unusual further reduction might be caused by the relatively short monitor period. Unlike before and right after the training, when data of six weeks were recorded, only one week was monitored in the long-term experiment. Meanwhile, the traffic condition may also vary after six months, which could potentially cause this issue.

Figure 2.5. Driving simulator by Sullman et al. (2015)

Although mainly targeting at specific type of drivers, these simulator-based studies have been proven effective in promoting eco-driving. Therefore, it would be beneficial to investigate the expansion of such devices. As the complexity and cost of such simulators can vary significantly, it is hence necessary to explore a possible option, which can balance the simulation realness and cost. While the simulation realness is positively correlated with the cost and complexity of the device, it is potentially feasible to develop a relatively low-cost simulator that can satisfy the minimum requirement of realness. Thus, following research is recommended to compare the architectures of existing simulators and the evaluations of their realness, and develop an affordable simulator that can be popularized to reach more end-users. Meanwhile, the evaluations on simulation sickness of existing simulators are also recommended. These results can help to justify the performance of their simulators and make their findings more convincing. The long-term effects of training programs should also be better monitored, and the influence of reinforcement learning after a long gap should be investigated. With a well-monitored long-term study and an effective reinforcement schedule, it will facilitate the promotion of eco-driving styles, especially for professional drivers.

2.4.3 Summary

All sharing the same aim of promoting eco-driving through training programs and campaigns, the located studies can be roughly divided into two groups based on their adopted approach, namely nationwide and simulator based training programs. Among the six identified nationwide training programs, it can be noted that they are mainly supported by governmental organizations and related enterprises, and intend to reach a large scale of end-users through their hosted learning sessions and campaigns. These training programs are education-oriented, and aim to raise public awareness of eco-driving. While they prevail in the effectiveness during the popularization to large scale of end-users, measuring the long-term effect of this type of training programs is difficult to implement. Meanwhile, it is indicated that the lack of repetitive training can lead to deteriorated driving performance over long term. Most importantly, these nationwide training programs have a high requirement on the budget and the financial revenue is nearly impossible to foresee. Therefore, this type of training programs is mainly supported by governmental organizations concerning the environmental impact of transportation. The unforeseen financial revenue could restrict the popularization of these programs among most related enterprises.

Meanwhile, five simulator based training programs were also located from the reviewed studies. Unlike the former group, these training programs are more research-oriented. Along with the introduction of eco-driving tips, this type of training programs focuses on replicating the on-road driving scenarios, and can measure most driving-related parameters with a high accuracy. Therefore, these training programs are mainly operated by relevant research groups, targeting primarily at commercial drivers. The major benefits of this type of training programs are the well-monitored driving performance, accurate evaluation of the eco-driving training, and the promising financial revenue from the cooperation with commercial transportation companies. Moreover, it is also easier to monitor the long-term effect of eco-driving training in these programs. However, it should be noted that seeking the balance between the simulator's complexity and realness could be rather difficult. Therefore, future research should evaluate the correlations between architecture complexity and simulation realness, and develop affordable simulators with satisfying realness that can be popularized to more end-users. Moreover, the simulation sickness of these simulators should also be evaluated to facilitate the investigation into the transferability of eco-driving trainings from simulation studies to real world driving conditions.

2.5 In-vehicle assistance tools

While training programs can effectively achieve an average fuel saving of approximately 10%, its large-scale popularization is still constrained. This is mainly because most existing training programs either are for research purpose or supported by relevant associations, and its commercial application is not applicable due to the budget of developing those simulators. Moreover, although Sullman et al. (2015) recorded a further reduction after six months of the training, most research found less dramatic reductions in long-term experiments. Thus, drivers need to participate in training repeatedly to maintain an optimised fuel economy.

In-vehicle assistance tools were hence developed as an alternative solution. It can promote eco-driving style by providing real time audio, visual or tactile feedback to drivers. The necessity of developing such tools has been recognized since 1986 (Greene, 1986). He suggested developing a simple and inexpensive device, which can provide drivers real time fuel consumption information without being a distraction. Several assistance devices have been developed and evaluated using either driving simulators or on road tests. These devices can be roughly divided into two groups based on their hardware platforms, which are external devices and smartphones.

2.5.1 External devices

Most researchers developed in-vehicle assistance tools as complete devices, which can utilize sensor measurements from the vehicle. As audio feedback alone tends to distract driver’s attention, most devices can provide tactile, visual or mixed advisory messages.

For tactile feedback devices, the most common approach is to develop an active acceleration pedal, which can generate counterforces under certain circumstances. For example, Várhelyi et al. (2004) focused on reducing speeding behaviours, and their pedal will be activated after breaking speed limits. Meanwhile, Birrell et al. (2013) aimed to minimize harsh accelerations, and developed a pedal that can vibrate and generate a force feedback when exceeding a predefined acceleration threshold. Owing to the convenience and potential benefits, necessity of developing haptic accelerator pedals has been widely approved (Nissan, 2008; Larsson and Ericsson, 2009; Continental, 2010; Birrell, 2013), and various haptic accelerator pedals with different mechanisms were hence developed. To find the best mechanism, Jamson et al. (2013) evaluated three feedback systems using a simulator. They first assessed a force feedback system, which introduces external forces when exceeding the threshold. Meanwhile, a stiffness feedback pedal that can change spring stiffness was evaluated subsequently. Afterwards, they also examined an adaptive stiffness system, which differ the transition from cruise to accelerate. Twenty participants were asked to follow target accelerator pedal position using the simulator, and it was found that force feedback pedal prevails in terms of user satisfaction and performance. Therefore, force feedback is more recommended when developing such devices. However, it should be noted that haptic accelerator pedals will increase in dimension, and are easier to be installed during manufacturing. Therefore, it will be more suitable for new vehicles. While this may restrict its popularization, a major advantage of tactile feedback devices is the least distraction. As indicated by Birrell et al. (2013), drivers only perceive little extra workload when performing eco-driving with the device activated, and can concentrate more on anticipating the traffic.

For visual feedback devices, they can either give direct advices or warn misbehaviours with indicators. A typical device was developed by Voort and Dougherty (1998). Their device requires some ECU information as input, such as vehicle speed, engine speed, gear position, steering angle, headway, and pedal positions. During the assessment in driving simulator (van der Voort, 1999) and field experiment (van der Voort, 2001), it was found that together with eco-driving instructions, this device achieved 16% and 11% fuel savings respectively. Although the total fuel saving in field test was less than in simulator, the general fuel reduction was still promising. Moreover, the introduced extra demands on drivers were also examined and it was found that the total workload perceived by the drivers was still within the mental effort. With most generated advices focusing on gear shifting, this device has been proven effective in promoting eco-driving, especially in urban areas. Meanwhile, an important feature of this device is the open configuration for different vehicle models, such as fuel consumption map, gear ratios and vehicle weight. While this is quite rare in similar systems, it can improve the accuracy of generated advices. Moreover, the evaluation in field experiment also indicated its transferability to real world, which is crucial to ensure it will not distract users from driving.

Meanwhile, Wu et al. (2011) also developed a visual feedback device. Unlike previous study, while their device only requires speed and acceleration information from vehicles, it also needs environmental information from external sensors, such as current speed limit, headway distance to preceding vehicle or traffic light, and traffic light duration. This system focuses on optimizing acceleration, and its visual guidance is provided as a floating dash line on a colour bar. While it achieved fuel savings between 22% and 31% among 8 participants in the simulator experiment, its application in real world is doubtable. This is because the developed HMI needs drivers' concentration on the moving display, and will tend to distract drivers' attention. Therefore, the driver safety will be a potential issue when using this system in practical. Nevertheless, the developed algorithm is especially suitable for autonomous vehicle applications and can be easily integrated with other control strategies.

Apart from these single mechanism feedback systems, several mixed mechanism devices are also developed. A typical research was conducted by Hari et al. (2012). They developed an on-board visual and audible feedback device to monitor vehicle acceleration, which can urge drivers to reduce aggressive behaviour and drive in a more eco style. This device was validated in field trial, with 15 light commercial vehicles tested for 4 weeks. An average of 7.6% fuel saving was achieved. While this saving is relatively smaller than other devices, it can effectively reduce aggressive behaviours. More importantly, this device is easy to be mounted on the vehicle, and has already been commercialized with an acceptable price. Meanwhile, Daun et al. (2013) also developed a device with visual and audio feedbacks, which focuses on heavy commercial vehicles. In the simulator experiment, an average of 12.6% fuel reduction was achieved among 40 participants. Moreover, their device was also integrated into a tractor for field trial (Heyes et al., 2015). Although the actual fuel reduction was not recorded, its performance of generating suitable advices was validated. Along with providing traditional retrospective advices, their system can also generate predictive advisory messages based on vehicle sensory measurements and digital map data. It can hence encourage an anticipatory driving style to further reduce fuel consumption.

Unlike previous studies, Staubach et al. (2014a) developed an eco-driving support system with visual and haptic feedbacks. This is because they found this combination had the fastest reaction time and smallest deviation (Staubach et al., 2014b). Through identifications of traffic lights and traffic signs, their device can provide advices on gear shifting and pedal control. This device was validated in simulator experiment, with an average of 16% fuel saving in urban scenario, and 18% in rural. This combination of feedbacks is inspiring, as the haptic feedback can alert drivers to watch visual interface. This setting can enable drivers to focus more on traffic anticipation, until driving circumstances change. While further investigations are still needed, it is a viable solution to reduce the potential distractions caused by visual feedback.

Although the existing research on developing external devices to promote eco-driving is still limited, there have been a growing trend to develop and commercialize them. While most studies are promoted by governments, some companies also notice the potential profits beneath such products. For new vehicles, the best option is to incorporate haptic pedal with vehicle console to provide mixed feedbacks. Meanwhile, devices with combined visual and audio feedbacks are more recommended for existing vehicles. Moreover, the marketing crisis of such devices should also be noted. As suggested by Staubach et al. (2014b), while participants approved the performance of such devices, most of them would not spend more than €300 on purchasing them. Despite the environmental benefits, the modest economic benefit of eco-driving is a long-term accumulation. Therefore, it requires a rather long time of driving to redeem the investment on such devices, which is not favoured by most drivers. Therefore, the production costs of such devices should be minimized, and relevant government support may be beneficial.

2.5.2 Smartphone based devices

As an alternative solution, some researchers preferred to use smartphones as the development platform to mitigate the marketing crisis of external devices. Owing to the rapid development of smartphones, multiple sensors have already been integrated, such as accelerometer, gyroscope, magnetometer, GPS and camera (Johnson and Trivedi, 2011). These sensory measurements can hence be fused to detect misbehaviours and provide feedbacks to drivers. Therefore, smartphone based assistance tools are more cost-effective compared with complete external devices. It only requires purchasing the app and an immobilize dock. While utilizing smartphones to promote eco-driving is relatively new, there have already been some previous research of monitoring driver behaviours with smartphones. For instance, Bergasa et al. (2014) and You et al. (2013) each developed an app for detecting inattentive and drowsy driving behaviours based on iPhone and Android platforms separately. Along with other driving safety research, they validated the potential of using smartphones to improve driving style.

Meanwhile, some previous smartphone based driving style optimisation studies were also identified and reviewed. As shown in table 2.4, there have been two studies on IOS platform and three on Android. Moreover, it should be noted that there is another research also identified but not included in the table, which is because its implementation platform is not specified. It is the MobiDriveScore developed by Chakravarty et al. (2013). It can use measurements from accelerometer and GPS sensor to detect risky manoeuvres, such as hard bump, hard cornering and harsh acceleration/deceleration. Meanwhile, driving performance was also assessed using the risk classification method proposed by Toledo et al. (2008). From these listed studies, it can be noted that they all emerged after 2011, which indicates the growing interest in promoting eco-driving in recent decades. While the exact research focus varies slightly among these studies, they all demonstrate the feasibility of using smartphones to improve driving style.

Table 2.4. Smartphone studies summary

Platform	IPhone		Android		
Author	Johnson & Trivedi	Paefgen et al.	Stoichkov	Astarita et al.	Castignani et al.
Time	2011	2012	2013	2013	2015
Aim	Driving style recognition based on critical events detection	Performance evaluation by comparing with IMU on critical events detection	Driving style recognition and provide feedback for detected bad manoeuvres	Improve driving style by estimating fuel consumption	Detect risky driving events and provide a representative score
Sensors	accelerometer gyroscope magnetometer GPS rear-camera	accelerometer GPS gyroscope	accelerometer magnetometer gyroscope	GPS	accelerometer magnetometer gravity sensor GPS
Function	Detect hard turns, swerves, harsh speed change	Detect hard turns, harsh speed change	Detect hard turns, sudden lane changes, and harsh speed change	Use correlation model and kinematic data obtained from GPS to estimate fuel usage	Detect over-speeding, acceleration, braking and steering
Feature	Sensor fusion; Use Dynamic Time Warping to detect events	Investigate influence of mounting position; Compare with accurate sensors	Sensor fusion; Compare with other users	Instantaneous fuel provided as feedback; Connected with a sever to process data	Sensor fusion; Detect event with fuzzy system; Consider time and weather

Meanwhile, the research conducted by Paefgen et al. (2012) is particularly important in this aspect, as they focus on the validation of smartphone measurements. Moreover, Johnson and Trivedi (2011), Stoichkov (2013), and Castignani et al. (2015), all performed sensor fusion to compensate the drawbacks of each individual sensor. This is recommended because sensory measurements can be noisy, and sensor fusion is an efficient optimizing solution. Meanwhile, as the accuracy of instantaneous fuel consumption estimation was promising (Astarita et al., 2014), it should be considered by other researchers as an additional feature. Presenting the instantaneous fuel consumption to drivers can improve their awareness of eco-driving, although the introduced distraction and extra workload needs to be assessed. Moreover, the event detection algorithm of Castignani et al. (2015) should also be noted. Unlike other studies, which use fixed-threshold based event detection, they developed a fuzzy system to consider all sensory measurements simultaneously. Meanwhile, their research also removes the restriction on initial pose of the mobile phone, and is the only study to consider weather and time of the day, which can influence drivers' psychology.

Along with these research-oriented apps, several commercialized apps were also developed. These apps use fewer sensors and can only provide real time advices. Examples of such applications are: DriveGain, Green Gas Saver, greenMeter, BlissTrek and iEcoMeter for the iPhone platform; Green Driving Gauge, Mileage Genie and Speedometer for the Android platform (Tulusan et al., 2011). Tulusan et al. (2012) conducted an extensive evaluation of most of these applications and selected DriveGain for field test. They suggested that DriveGain could provide high quality feedbacks and allow convenient access to collected data. It can provide advices on gear shifting and vehicle speed. A general journey score can also be presented to the driver. Fifty professional drivers participated their field trial, and an average of 3.23% fuel saving was achieved with the app. An important feature of this research is the optional usage of this app, as drivers can decide the frequency and length of using it. Therefore, this may be the reason of the smaller fuel saving. Nevertheless, this research validated the performance of a commercialized smartphone app, which only costs £3.99.

While these solely smartphone based apps can promote eco-driving, there has also been a trend of developing smartphone apps that can extract data from vehicle's ECU. This growing trend is caused by the appearance of Bluetooth OBD-II connectors, which offer a cost-effective connectivity between smartphones and ECU. Unlike previous applications, smartphones in this kind of research is mainly a data processing centre, and the majority of vehicle state information is supplied by ECU. Instead of gathering measurements from its own sensors, the developed smartphone apps directly acquire data through the OBD-II connectors. Therefore, smartphones are mainly treated as a data processing platform, and hence requirements on smartphones are reduced. For instance, most single smartphone research requires smartphones to be properly mounted and calibrated to eliminate bias in the measurements. Moreover, data collected from vehicle's ECU is more accurate than smartphone sensors. Furthermore, more detailed vehicle state data, such as fuel consumption, throttle/brake position and engine speed, can be easily obtained, allowing data processing to be more accurate. Several previous studies are hence identified.

A typical research was conducted by Araujo et al. (2012). Their app is based on Android platform. It can acquire vehicle state data, such as speed, acceleration, altitude, throttle value, instant fuel consumption and engine speed through an OBD-II Bluetooth adapter. With these acquired data, they developed three classifiers to evaluate driving styles and generate corresponding advices. The first classifier is to identify driving condition, such as urban, highway or combined. Meanwhile, the second classifier performs fuzzy logic to evaluate fuel consumption of current driving style. Afterwards, the third classifier uses fuzzy logic to select a suitable hint based on the results of two previous classifiers. A preliminary evaluation of this app was implemented using a VW Sharan. It was found that this app could accurately detect driving conditions, evaluate fuel consumption and hence provide correct hints. Although the actual reduction of fuel consumption was not evaluated, this app was proved useful for promoting eco-driving. However, a potential crisis of this app lies with the first classifier, which determines driving conditions by comparing the average speed with two thresholds. The accuracy of this linear discriminant can be vastly influenced by traffic congestion or other similar situations. Therefore, this app may misjudge the current driving condition, which will have an adverse influence on generating a correct hint.

Meanwhile, another similar research was implemented by Meseguer et al. (2013). Their app is called DrivingStyles, and is based on Android platform. Smartphones in this research were treated as a communicating platform. This app can acquire vehicle state information from ECU and then upload them to a website data centre. A neural network was developed to identify driving conditions and driving styles based on vehicle speed, acceleration and engine speed. This app has been popularized to public and its performance was validated with customers. However, a major crisis of this app is that it cannot provide real time feedback to drivers. While vehicle state data is recorded during the driving, it needs to be uploaded to the server for analysis afterwards. Drivers can only access the analysis through the website after the drive is finished. Although hints on improving driving styles are also provided on the website, the lack of real time feedback will limit the impact of this app.

Furthermore, Magaña and Organero (2011) also developed a smartphone app called Artemisa based on Android platform. Unlike previous two studies, their app acquires data from both smartphone sensors and vehicle's ECU, and more trust is put on the former data source. This setting is to make the app more robust as some vehicle's sensor data is not accessible. Additionally, this combination of data source also provides more information than vehicle state measurements alone, such as weather and road state. The acquired data is then analysed using an expert system to generate proper eco-driving advices. Afterwards, the eco-driving tips are presented in both visual and audio forms to alert the drivers. The evaluation of driving style in this app is more accurate as it considers weather and road state conditions. More importantly, both data sources are obtained through smartphone's web service. This data acquisition approach is cost-effective and hence can be easily adopted by other similar studies.

While developing smartphone apps to promote eco-driving is a newer trend, with most instances occurred after 2011, it is easier to popularize and much cheaper than complete devices. Although the individual fuel saving is smaller than other approaches, it can still be significant with a large scale of users.

Therefore, government supports or promotional activities of such apps would be beneficial. Moreover, while both using smartphone sensors and incorporating ECU are validated in promoting eco-driving, the latter option is more recommended as it can reduce the requirements and restrictions on smartphones. Moreover, the ECU measurements are more accurate and can reduce the processing workload of smartphones. Thus, incorporating ECU and smartphone could be a promising research area, and following studies are recommended to further evaluate the exact influence of such apps and add more feature functions, such as the review and comparison of trip data proposed by Stoichkov (2013).

2.6 Chapter summary and conclusions

Extensive research efforts have been devoted to investigating different driving styles, both from Psychology and Engineering backgrounds. While most studies focus on the safety aspect, the variation of fuel consumption caused by different driving styles is also widely accepted. As there have been extensive studies and applications aiming to investigate this relationship and hence promoting eco-driving, this review is proposed to summarize these implemented research and evaluate their contributions and limitations. Various aspects of driving styles and fuel consumption research are covered, such as definitions and classifications of driving styles, as well as training programs and in-vehicle assistance tools adopted to promote eco-driving.

While the concept of driving style can be easily interpretable, it was found that there is currently no consensus on a unified definition of driving style. Through a comprehensive search in relevant literature, ten different definitions of this concept were located. An initial comparison was implemented to distinguish driving style from driving behaviour, which is a broader concept mainly adopted by Psychology researchers. This is because there tends to be a misunderstanding between both concepts. Afterwards, a more detailed comparison among these ten definitions was conducted. It was found that while the exact forms of these definitions vary, the underlying essence is similar. Therefore, a generalised definition of driving style is proposed as the driver's own habitual choice of driving manoeuvre.

Afterwards, the typical classifications of driving style were also investigated. Through a literature search, fifteen sets of classifications proposed by different researchers were located. While the classification results vary significantly among these studies, several driving style types are commonly included, such as aggressive driving, normal driving, eco-driving, inattention driving and defensive driving. These representative driving styles were hence separately described. Moreover, some classification approaches were also reviewed. The most commonly used driving style classification approaches are identified as neural network, clustering techniques, fuzzy logic and jerk-based techniques.

Furthermore, sharing the same aim of promoting eco-driving and hence minimizing fuel consumption, these identified studies can be roughly divided into two groups based on the adopted mechanism, which are training programs and in-vehicle assistance tools. The first group, training programs, are mainly conducted by governments and other related organisations. It tends to be medium to large-scale campaign, aiming to promulgate policy, develop eco-driving rules, host popularize events, and conduct on road training sessions. Several nationwide training programs were identified. While the majority of these programs were held in Europe, there were also separate programs in Singapore and Japan. Meanwhile, some research institutes also proposed driving simulator based training programs, mostly aiming at specific types of drivers. While the positive outcomes of these programs have been widely confirmed in various instances, a major crisis of this type of eco-driving promotion approaches is the large-scale popularization. This is because there is a high demand on the budget to develop simulators and host campaigns, which hence constrains its commercial applications. Moreover, most studies also found the training effects of these programs tend to decay over time. Thus, repetitive training is required to maintain a satisfying eco-driving performance of interested participants. This requirement can also restrict its popularization as it will occupy more time of those participants, and related training facilities.

Therefore, these issues should be addressed in future research to improve the feasibility of these eco-driving training programs.

Designing in-vehicle assistance tools is also identified as a useful approach to promote eco-driving. Unlike training programs, which tend to have weakening long-term effects, these devices can provide real-time feedback to drivers and hence improve driving style consistently. Two types of in-vehicle assistance tools were identified, which are external complete devices and smartphone-based devices. While the former can provide various kinds of feedback, it has a marketing crisis due to the price and user acceptance. Meanwhile, smartphone based devices can be an affordable option for promoting eco-driving, especially when vehicle state data can be acquired from the vehicle's ECU through cost effective Bluetooth OBD-II connecters.

From reviewed studies, it can be noted that different driving styles can have significant influence on the variations of fuel consumption. While there have been extensive studies aiming to reduce fuel consumption through optimised driving style, ranging from conducting eco-driving training programs to developing in-vehicle assistance devices, there has been no consensus on the exact influence of this human factor, and lack of repetitive studies to demonstrate the evidence. As human behaviours tend to be volatile, causing variations in repetitive research, it would hence be beneficial to develop a humanized and personalised driver model that can mimic specific human drivers to facilitate following studies.

Chapter 3 – *Review of driver modelling approaches*

This chapter reviews the existing research on various driver-modelling approaches. Following the systematic literature review method, a sum of 48 articles was located in six electronic databases. Identified studies can be roughly classified into two groups based on their adopted methodology, namely numerical models and data-driven models. More detailed subgroups are also derived within each major group. Afterwards, both the selected perception parameters and modelling methodology are discussed to investigate the potentially best option for developing such driver models. It has been found that while both numerical and data-driven models can be adopted to develop humanized driver models, their performance and applicable study vary significantly. While the numerical models are more computational efficient, their performance in replicating humanized behaviours needs more thorough evaluations. Meanwhile, data-driven models prevail in the potential and performance of simulating human driving behaviours, but suffer from the high requirements on the computation complexity.

The main content of this chapter has been submitted in the form of a review article to the Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering.

3.1 Introduction

While there have been many studies attempting to reduce fuel consumption through the optimisation of driving style (Cziko, 1989; James et al., 2004; Chatzikomis and Spentzas, 2009; Filev et al., 2009), it should be noted that the individual variation of driving style still has not been precisely determined. This is mainly caused by the unrepeatable nature of human behaviours, making comparative study difficult to implement. Therefore, a viable solution of this issue is to develop personalised driver models that can mimic specific human drivers with high repeatability. With these personalised driver models, the individual variation of those human drivers can hence be evaluated in normalized conditions. However, it should be noted that based on a preliminary literature search, the existing studies on developing personalised driver models are rather limited. As the major focus of developing these personalised driver models is to replicate the driving behaviour of each individual driver, a mitigation solution is hence identified as developing driver models that address human factors, which can be generalised as humanized driver modelling. Therefore, the personalisation of these humanized driver models can be easily achieved through the calibration with sufficient individual driving data. Thus, this literature review aims to evaluate the existing studies on developing humanized driver models.

Along with the contribution to investigating individual driving style variations, the development of humanized driver models can also advance current research on traffic simulation (Kesting et al., 2007; Ossen and Hoogendoorn, 2007). From the perspective of microscopic traffic simulation, these driver models can facilitate research investigating the influence of driving style on the physical attributes of the vehicle (Lefèvre et al., 2015a; Bolduc et al., 2017; Zhang et al., 2017). Moreover, incorporating and assigning different driving styles to multiple vehicles can further improve the heterogeneity research in macroscopic traffic simulation (Tang et al., 2014). Therefore, it can be noted that the incorporation of these humanized driver models can increase the variety of traffic simulation at both microscopic and macroscopic levels, which can also improve the similarity to real traffic flow.

While developing humanized driver models can potentially benefit both eco-driving and traffic simulation research, the existing studies on this topic are rather limited. Therefore, a structured review of literature on humanized driver modelling was conducted to shed light on the current research status and future directions. The main research questions addressed in this review are:

- What are the approaches adopted to develop humanized driver models?
- What contributions can these models make?
- What are the main paths for further research on humanized driver models?

3.2 Literature review methodology

As indicated by Tranfield et al. (2003), a systematic literature review is a method that adopts a replicable, transparent and explicit procedure to minimize the potential bias during the literature review process. It typically consists of five phases: (1) formulating question, (2) locating studies, (3) selection and evaluation, (4) study analysis, and (5) report findings (Denyer and Tranfield, 2009). While the first phase has already been introduced in section 3.1, the second and third phases will be addressed in this section.

3.2.1 Location of studies

In order to locate relevant studies on humanized driver models, four sets of keywords ("driving style", "model", "fuel", and "car following") were first identified as research pillars. While "driving style", "model", and "fuel" were directly revealed in the proposed research focus, the selection of "car following" was based on its relevance to the research question. Initially proposed by Reuschel (1950) and Pipes (1953) over fifty years ago, car-following modelling is an essential component of microscopic traffic simulation (Khodayari et al., 2014). It mainly refers to the driver's control of the following vehicle's longitudinal movement under the influence of the preceding vehicle, while preserving a preferred headway distance (Hao et al., 2016). This regime is a prominent scenario for driving style investigations as both the driver's cognition and action characteristics can be reflected in the preferred headway distance and driving patterns. Moreover, it also has a high correlation with the design of ACC, which many personalised control strategies have been proposed to address the individual driving style difference. Therefore, "car following" was also included as a research pillar.

With identified four research pillars, different combinations of them were constructed to form the search strings of this study, as shown in table 3.1.

Table 3.1. Search pillars

Group	Search string
Pillars 1+2	"driving style" AND "model"
Pillars 1+4	"driving style" AND "car following"
Pillars 2+3+4	"model" AND "fuel" AND "car following"

Along with the search strings, the locating of relevant articles was conducted in six electronic databases, including Engineering village compendex, Web of Science, IEEE Xplore, SAE Mobilus, ASME, and Scopus. These online databases were selected due to their relevance to the proposed study. It should be noted that while overlaps can occur during the search, the inclusion of six databases can help to ensure all relevant articles that fell within the searching criteria were included. In order to ensure the reliability and availability of sources, search results were limited to articles published in academic journals and proceedings of international conference only.

3.2.2 Selection and evaluation

Searching the predefined search strings in the abstract part within each database, a sum of 1158 articles was located in the initial search. Afterwards, a pre-selection was conducted by screening the titles and abstracts. Only articles focusing on modelling different driving styles were selected. Therefore, articles addressing the driving style difference from the psychology perspective were discarded. This process ended up with 99 papers selected, as shown in table 3.2.

Table 3.2. Number of publications per database

Search string / Database	Pillars 1+2		Pillars 1+4		Pillars 2+3+4	
	Final	Initial	Final	Initial	Final	Initial
EI Compendex	9	157	1	14	11	82
Web of Science	11	178	1	12	8	104
IEEE Xplore	7	59	1	4	2	20
SAE Mobilus	2	31	0	0	0	7
ASME	1	27	2	29	1	10
Scopus	23	312	6	28	11	84

After duplicates being excluded, 43 articles that complied with the selection criteria were located. Meanwhile, another 5 papers were also included using the snowball approach, resulting in a final selection of 48 articles.

3.3 Finding and analysis

With the selected 48 articles, descriptive analysis was implemented first to address the publication trend and source of these studies. Afterwards, the identified studies were divided into seven groups according to their adopted modelling methodology. A detailed content analysis and model evaluation was then conducted.

3.3.1 Descriptive analysis of findings

Figure 3.1 presents a preliminary descriptive analysis of those selected publications. It can be noted from figure 3.1 that driving style modelling has gained increasing research interest since 2015, with 28 papers (58.3%) published in the following 4 years. This growing trend suggests that driving style modelling is a relatively new and emergent research field, which has already gained popularity in recent years. Meanwhile, the advancements in driving data collection techniques and ADAS in recent years also boost the relevant studies. Moreover, it can be noted that the numbers of articles published in journals and conferences are roughly the same, with two more papers published in journals. Meanwhile, Physica A (5 papers) and IEEE Intelligent Vehicle Symposium (5 papers) are the largest publication sources for journal and conference papers respectively. The variety of publication sources also demonstrates the fact that driving style modelling is an emerging topic, as it can be accepted by a wide range of sources, with no specialised journals or conferences found.

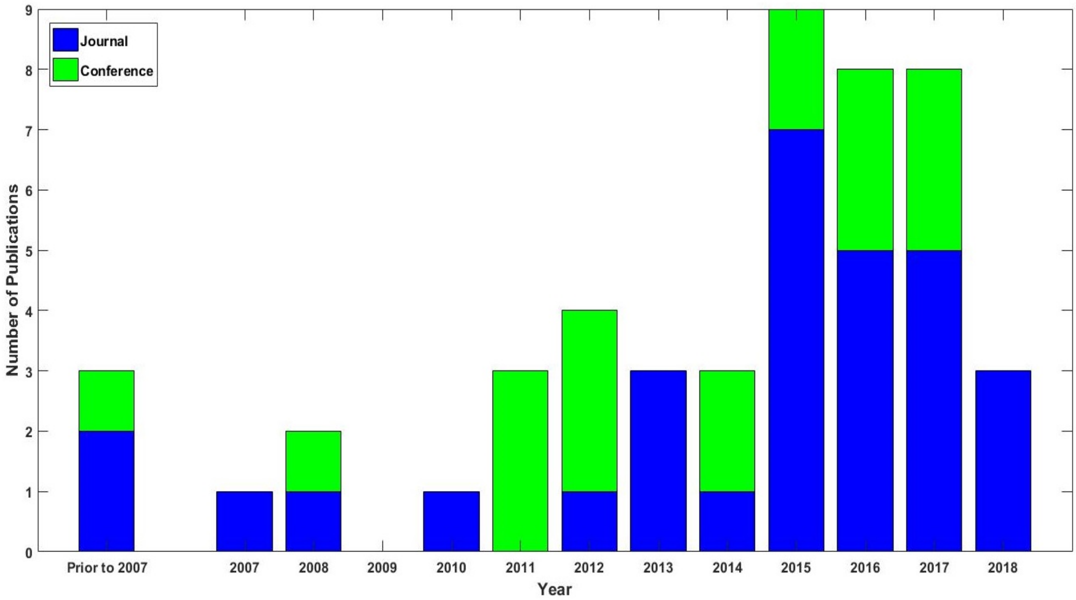


Figure 3.1. Number of publications per year

3.3.2 FVD based models

Among the reviewed articles, FVD is identified as the most commonly used formula-based model, with seven located publications. Initially proposed by Jiang et al. in 2001, FVD model was designed specifically for car-following regimes (Jiang et al., 2001). Its general form can be described as,

$$\frac{d_{v_n}}{dt}(t) = \kappa[V(\Delta x_n) - v_n(t)] + \lambda \Delta v_n \qquad \textbf{3.1}$$

Where:

κ	Sensitivity constant
$V(\Delta x_n)$	Optimal velocity function of the headway
$v_n(t)$	nth vehicle’s speed
λ	Sensitivity
Δv_n	Relative speed between nth vehicle and its preceding vehicle

While no driving style difference was included in the original form, this individual characteristic was incorporated in a number of new models developed upon FVD. For example, Tang et al. (2014) incorporated individual preference on optimal speed and safe distance into the FVD model as additional driver attribution. They defined optimal speed as

$$V(\Delta x_n) = \begin{cases} v_{n-1}(t)\{1 + \tanh[C \times (\Delta x_n(t) - \Delta x_c(t))]\} & if\ \Delta x_n(t) < \Delta x_c(t) \\ v_{n-1}(t) + (v_{max} - v_{n-1}(t)) \times \tanh[C(\Delta x_n(t) - \Delta x_c(t))] & else \end{cases} \quad \textbf{3.2}$$

and safe distance as

$$\Delta x_c(t) = (1 + r) \cdot max\left\{h_{c,stop}\ , v_n(t)t_w - \frac{(v_n(t))^2}{2a_{n,min}} + \frac{(v_{n-1}(t))^2}{2a_{n-1,min}} + h_{c,stop}\right\} \quad \textbf{3.3}$$

Where:

C	Sensitivity coefficient for safety distance
$\Delta x_c(t)$	Preferred headway distance
v_{max}	Maximum vehicle speed
r	Driving style category
$h_{c,stop}$	Safety distance when preceding vehicle stops
t_w	Reaction time when preceding vehicle stops
$a_{n,min}$	Vehicle's maximum deceleration

Meanwhile, five separate studies were conducted by Yu et al. to investigate the impact of various factors on car-following behaviours, such as speed fluctuation of one (Yu et al., 2016) and multiple leading vehicles (Guo et al., 2017), headway changes (Yu and Shi, 2015a; Yu and Shi, 2015b), and relative speed fluctuation (Yu and Shi, 2016). Additional term representing each factor was incorporated with the conventional FVD model. The speed fluctuation of one leading vehicle was defined as (Yu et al., 2016),

$$\gamma[v_{n-1}(t) - \overline{v_{n-1}(t-m)}] \quad \textbf{3.4}$$

The term describing speed fluctuation of multiple leading vehicles was (Guo et al., 2017),

$$\sum_{j=1}^{N} \gamma_j \left[v_{n-j}(t) - \frac{1}{m}\sum_{k=1}^{m} v_{n-j}(t-k)\right] \quad \textbf{3.5}$$

Two models considering headway changes were also developed, one concerned with the memory effect, and was defined as (Yu and Shi, 2015a),

$$\gamma[\Delta x_n(t) - \Delta x_n(t-\delta)] \quad \textbf{3.6}$$

The other model incorporated the fluctuation of headway gap as (Yu and Shi, 2015b),

$$\gamma[\Delta x_n(t) - \overline{\Delta x_n(t-m)}] \quad \textbf{3.7}$$

Meanwhile, the relative speed fluctuation was described as (Yu and Shi, 2016),

$$\gamma\left[\Delta v_n(t) - \frac{1}{m}\sum_{k=1}^{m}\Delta v_n(t-k)\right] \quad \textbf{3.8}$$

Where:

γ,γ_j	Sensitivity parameters
m	Time window length
N	Number of considered leading vehicles
δ	Memory step

Another identified study was implemented by Zhang et al. (2017), which they considered the acceleration of the leading vehicle and the driving style of host driver. Their improved FVD model was defined as,

$$\frac{dv_n}{dt}(t) = a[V(\Delta x_n(t)) + \tau V'(\Delta x_n(t))\Delta v_n(t) \cdot (p_1\alpha + p_2\beta + (1-\alpha-\beta)p_3) - v_n(t)] +$$
$$\lambda[\Delta v_n(t) + \tau\Delta a_n(t) \cdot (q_1\alpha + q_2\beta + (1-\alpha-\beta)q_3)] + ka_{n-1} + O(\tau^2) \quad \textbf{3.9}$$

Where:

a	Driver's sensitivity
τ	Delay time
α,β	Influence coefficients of intensity among three driving styles
p_1,p_2,p_3	Anticipation ability coefficients of each driving style for headway distance
q_1,q_2,q_3	Anticipation ability coefficients of each driving style for speed difference
k	Response coefficient to the leading vehicle's acceleration
a_{n-1}	Acceleration of the leading vehicle

Both Tang et al. (2014) and Zhang et al. (2017) divided driving styles into three groups, and extracted the features of each group to establish the respective driver models (aggressive, neutral, conservative). The established models were assigned to 100 vehicles to examine their effects through traffic simulation in both studies. It was found that the developed models could effectively improve the stability and realism than the conventional FVD models. Moreover, Tang et al. (2014) also evaluated fuel consumption and exhaust emission of different driving styles, and found that homogeneous traffic flow consisting of aggressive drivers consumed more fuel than that of conservative drivers. Meanwhile, they also noticed a high correlation between heterogeneous traffic flow and neutral driver, which indicates that the interactions between drivers with different driving styles can have a huge impact on the traffic flow.

Meanwhile, although those five studies conducted by Yu et al. used essentially the same dataset, no cross comparisons were made between their proposed models. Nonetheless, all studies reached a similar conclusion that the inclusion of the transit dynamics of the leading vehicle could effectively improve traffic stability and reduce fuel consumption.

3.3.3 Model predictive control based models

Along with the FVD based models, MPC was also extensively used in identified studies to develop numerical models. Initially proposed in 1960s, MPC is an advanced approach for process control while satisfying predefined constraints (Garcia et al., 1989). The kernel of MPC is based on iterative, finite-horizon optimisation of a plant model. As a multivariable control algorithm, it mainly consists of three components, which are an internal dynamic model of the process; a history of past control moves; and an optimisation cost function over the receding prediction horizon (Morari and Lee, 1999). As MPC allows constraints to be introduced in natural forms, it has been extensively used in process control applications. Through the location of studies, a total of five studies were identified, with four focusing on ACC design (Luo et al., 2010; Zhang and Vahidi, 2011; Shakouri et al., 2015; He et al., 2017) and one concerning only gear selection (Jing et al., 2016).

Among the four MPC-based ACC algorithms, Luo et al. (2010) considered safety, comfort, fuel consumption, and car-following performance as additional constraints. Meanwhile, the pre-planned acceleration and deceleration commands were incorporated to smooth the transition dynamics of the vehicle in the model developed by He et al. (2017). Both models were evaluated through the comparison with the conventional ACC algorithm. It was found that both proposed systems could effectively improve the driving comfort and fuel economy through reductions in acceleration, jerk, and fuel consumption.

Another similar study was implemented by Zhang and Vahidi (2011). While they did not focus on the driving style personalization, their study concerned the adoption of eco-driving strategies. An interesting contribution of this work is the attempt to predict the leading vehicle’s behaviour. This feature was then incorporated into their MPC model to estimate the immediate movement of the leading vehicle. Through simulation evaluation, this system was found capable of reducing fuel consumption effectively. While the driving style difference was not addressed in this study, the idea of predicting the leading vehicle’s movement can benefit the research on personalised driver modelling.

Meanwhile, in addition to the NMPC model, Shakouri et al. (2015) also developed a PI+GS and a B-BAC controller for the ACC system. All three controllers were evaluated under the same simulation scenarios. While all three controllers can satisfy the requirement for safety and car-following behaviour, the B-BAC was found the best option considering the driving comfort, fuel consumption and computational complexity.

Along with these ACC design studies, Jing et al. (2016) focused solely on optimizing gear selection with MPC to reduce fuel consumption. Their model can search for the optimal gear selection in the prediction horizon at each time step. Meanwhile, in order to improve the real time feasibility, they designed a PMP based deduction method to reduce the computation complexity. Through a 300s car-following scenario, this controller was validated to reduce fuel consumption by 14%, while maintaining a satisfactory driving comfort.

3.3.4 Other numerical models

In addition to the above commonly used approaches, several other numerical models have also been developed to simulate the human driving behaviour. For instance, based on the General Motors Nonlinear model (Gazis et al., 1961), Bolduc et al. (2017) developed an improved driver model for personalised ACC. They formulated vehicle acceleration as a nonlinear function of vehicle speed and headway distance, which can be described as,

$$\dot{v}_n(t) = \lambda \frac{(v_{n-1}(t-\tau)-v_n(t-\tau))}{\Delta d(t-\tau)} + \eta \left(\Delta d(t-\tau) - THW_\mu * v_n(t-\tau)\right)^3 \qquad \textbf{3.10}$$

Where:

λ,η	Driver gains
τ	Driver delay
THW_μ	Time headway

Using three trial data from a simulator, their model was assigned to perform different driving styles. While the obtained results showed different following behaviour, the actual similarity to human drivers was not evaluated.

Meanwhile, Zhai et al. (2016a; 2016b) incorporated two time delays in headway and velocity respectively to imitate the cognition process of human drivers during the car-following scenarios. While its similarity to real human drivers was not evaluated, they found the proposed model could effectively suppress traffic congestion and reduce fuel consumption during simulation. Their model was defined as,

$$\dot{v}_n(t) = a_n\left(F\left(y_{n-1}(t-\tau_1(t)), y_n(t-\tau_1(t)) - v_n(t-\tau_2(t))\right) + u_n(t)\right) \qquad \textbf{3.11}$$

Where:

y_n	Headway distance between nth and its preceding vehicle
a_n	Sensitivity of the nth driver
$\tau_1(t)$	Time delay for sensing headway difference
$\tau_2(t)$	Time delay for sensing speed difference
$F(n)$	Optimal velocity function

Another study was implemented by Ossen and Hoogendoorn (1999), which focused on the heterogeneity in car-following behaviour. This model was defined as,

$$\dot{v}_n(t) = \sum_{j=1}^{m_{1,n}} \alpha_n^{(j)} \Delta v_n^{(j)}(t-\tau_n) + \sum_{j=1}^{m_{2,n}} \beta_n^{(j)} \left(\Delta x_n^{(j)}(t-\tau_n) - S_n^{(j)}\right) \qquad \textbf{3.12}$$

Where:

τ_n	Driver's reaction time
$\Delta v_n^{(j)}$	Relative speed between car n and car j
$\Delta x_n^{(j)}$	Distance between car n and car j
$\alpha_n^{(j)}$	Sensitivity to relative speed difference
$\beta_n^{(j)}$	Sensitivity to headway distance difference
$m_{1,n}$,$m_{2,n}$	Number of considered leading vehicles
$S_n^{(j)}$	Desired headway distance

While driving style difference was not specified, they found that driving styles could vary significantly, resulting in a high degree of heterogeneity in car-following behaviour. Based on the collected traffic trajectory data, they modelled the impact of heterogeneity on traffic in car-following regimes. From a microscopic level, they found different driving style could have a huge impact on traffic dynamics. Therefore, along with individual fuel reduction, it can be noted that optimising driving style can also influence the associated traffic flow. A similar conclusion was also obtained by Kesting et al. (2007). Their model can detect current driving scenarios and modify ACC parameters according to different driving styles. Through a microscopic traffic simulation, they found the inclusion of such system could significantly improve traffic stability and performance.

Another interesting model was proposed by Bifulco et al. (2013). Instead of building models for different driving styles, their personalised ACC was designed to address the individual difference. Moreover, in their proposed framework, ACC can be calibrated during driving to learn the human driver's style and preference. The related parameters can be tuned during this process.

After the learning phase, the calibrated model can then perform more similar to the human driver. While their model was only validated in the post-processing phase using the collected on-road data, this proposed framework can be beneficial for other studies on driver model personalization.

Meanwhile, the driver models developed by Javanmardi et al. (2017) and Hellström and Jankovic (2015) were based on a feedback PI controller. While both models were created to simulate three specific driving styles (aggressive, normal/moderate, and eco/smooth), additional information, such as speed limit and road grade, were perceived only by the first model. A positive correlation between driving style and fuel consumption was found through simulation. Moreover, it was also confirmed that the individual differences on feedback mechanism tend to be the major cause of driving style variations.

While Tang et al. (2018) also focused on car-following scenarios, they mainly investigated the behaviour when approaching signalized intersections. With the overarching aim of minimizing idling time, they proposed a speed guidance strategy to optimise the traffic flow near the intersections. While no real world data collected, their model was evaluated through simulation, which an average fuel reduction of 15.2% was achieved.

Unlike previous studies, Todorut et al. (2016) only focused on the braking events, and attempted to evaluate the characterization parameters of the braking process. Their numerical braking model considered the personalised involuntary delay, which is the length of time elapsed from the moment when the driver perceives the danger, up to the time when the vehicle braking is constant. While further evaluation is still needed for the proposed method, the development of personalised braking models can be beneficial, especially when investigating regenerative braking component.

Meanwhile, another unique study was conducted by Shirazi and Rad (2012), which they investigated the steering behaviour of intoxicated drivers. Using Fatal Vision goggles to simulate the influence of alcohol, driving data of two human drivers (sober and drunk) were collected from a simulator. Four linear models (continuous-time, ARX, state-space, and Box-Jenkins) were then developed to imitate the lateral behaviour of drunk drivers. While this study focused on differentiating sober and drunk driving behaviours, a high correlation was found between drunk and aggressive drivers.

3.3.5 Fuzzy logic based models

Apart from the above numerical models, data driven models based on artificial intelligence are also commonly used to develop humanized driver models. Among all adopted artificial intelligence approaches, fuzzy logic is identified as one of the most commonly used method. Originally proposed by Zadeh (1965), fuzzy logic allows vagueness to be incorporated in the determination process. A fuzzy logic controller typically consists of five components, which are variables, rules, a fuzzifier, an inference engine, and a defuzzifier. Meanwhile, it also comprises four steps, initialization, fuzzification, inference, and defuzzification. Variables and rules are defined in the initialization phase. Variables are linguistic terms describing input and output, usually ranging from small to large. For each variable, it has a set of linguistic terms and associated membership functions. Meanwhile, rules are the logic linkage between input and output, and are used to determine correlating actions for each specific combination of inputs. Both parameters can be defined using expert's knowledge during the initialization. After the initialization phase, the actual inputs of the controller are transformed from crisp values to corresponding linguistic terms. Typically, two or more terms can be correlated with each single input, and the degree of involvement is determined by membership functions. With the fuzzified inputs and corresponding rules, an inference engine can be used to compute the contribution of each rule to the output. Finally, the accumulated output is transformed from fuzzy into crisp during the defuzzification phase. The major advantages of fuzzy logic are identified as (Godil et al., 2011),

- simplicity and flexibility
- can handle problems with imprecise and incomplete data
- can model nonlinear functions of arbitrary complexity

- cheaper to develop
- cover a wider range of operating conditions
- more readily customizable in natural language terms
- more similar to human reasoning

Following the proposed selection criteria, eight studies were located from the literature search. The first research was implemented by Zalila and Lezy (1994). They focused on car-following scenarios and developed a hybrid fuzzy and classical model. The incorporation of the fuzzy controller was found could effectively reduce abrupt speed changes, which was very common with the classical controller. While the fuzzy controller was not fully tuned, they obtained satisfactory results in both simulation and on-road tests. Another car-following model was developed by Kamal et al. (2008). A neural network was developed to calibrate the membership functions of their fuzzy controller. While a promising result was obtained through the comparison of a two-minute driving data, more evaluation of the proposed method is needed to justify its performance.

While Su et al. (2018) also focused on car-following scenarios, they developed models for three specific driving styles instead of personalised drivers. They first categorized 84 drivers into three driving style groups. Afterwards, the features of each group were extracted and used to calibrate the fuzzy rules and membership functions of three driver models. Through comparison with the collected data, they validated their models' performance in differentiating these three driving styles. However, the individual difference among those drivers in the same group was not investigated. Another similar study was implemented by Hao et al. (2016). They developed two generalised driving style models (aggressive and conservative) using selected vehicle trajectory data from a published dataset. The membership functions of each variable were calibrated using GA. The performance of the established models was validated through the comparison with the trajectory data of another two vehicles from the dataset.

Meanwhile, Khodayari et al. (2011, 2013) also developed two car-following models using different calibration approaches. In their first study, only the membership functions of driver reaction delay were calibrated from real data, and other input variables were normally distributed. While in the following study, they developed a neural network to estimate the fuzzy controller from the published driving dataset. Promising results were obtained through the comparison with the remaining data of the dataset. While no personalization was addressed in both studies, the proposed idea of differentiating the reaction time can be incorporated to facilitate the investigation into individual driving style variations.

Along with longitudinal control, lateral movements were also considered by Wang and Liaw (2014). The membership functions of their model were tuned using a multi-objective evolutionary algorithm. Promising results were obtained through the imitation of eight human participants on five tracks in car racing games.

Meanwhile, the fuzzy controller developed by Chai et al. (2017) only concerned with the car merging scenarios. They modelled the gap acceptance behaviour using a tuned fuzzy logic controller. The driver's personality and driving style were incorporated in the fuzzy system to improve its personalization and customization. Promising prediction accuracy was obtained through comparisons with field data.

3.3.6 Neural network based models

Owing to its performance in imitating human behaviours from the machine learning perspective, neural network is another widely adopted approach for human driver modelling, with six studies identified from the search of relevant literature. ANN originates from the computational model developed by McCulloch and Pitts (1943), which they modelled a simple neural network with electrical circuits. Meanwhile, the first supervised learning model was proposed by Rosenblatt (1958), with the concept of perceptron. As indicated by Cheng et al. (2016), a typical ANN often consists of three or more layers, with various numbers of neurons in each layer. The first layer interfaces with the real world to receive inputs to the model. One or more hidden layers are used to process the information while mimicking human brains. Afterwards, the output of the model is computed in the final layer and sent to the real world handler. According to Maind and Wankar (2014), the typical advantages of ANN can be described as,

- can derive meaning from complicated or imprecise data
- high ability of adaptive learning
- self-organization
- real time operation
- fault tolerance via redundant information coding

Among the seven identified studies, the earliest research was conducted by Macadam et al. (1998). They used a two-layer neural network to develop a personalised driver model in car-following regimes. Although only one driver model was calibrated, it has achieved satisfying results in the preliminary evaluation, revealing the promising potential of developing driver models using neural network.

Another research was conducted by Bifulco et al. (2008). They also focused on the car-following regimes and developed three driver models that based on ANN, linear function, and polynomial function respectively. Real driving data collected from an instrumented vehicle was used to calibrate the car-following models. The established three driver models were then evaluated using 30 minutes data. While no significant difference was found among the three models, the three-layer feedforward neural network model showed more flexibility in learning capabilities.

Meanwhile, Geng et al. (2016) also developed a three-layer ANN to model humanized drivers, but they concerned solely on turning events. They considered three types of turning events, such as left turn, right turn, and lane keeping/car-following on curvy roads. After training their ANN with real data from a naturalistic driving database, a satisfying result was obtained in simulating the human's turning behaviour. Moreover, they also found the selection of prediction step could have a huge impact on the model's performance.

Apart from the above three studies, the other four studies were conducted by the same research group (Shi et al., 2014; Xu et al., 2015; Shi et al., 2015; Shi et al., 2017). While their ultimate aim was to evaluate driving styles, personalised driver models were developed for normalization. In the first two studies, CMAC (Shi et al., 2014) and RBF (Shi et al., 2015) networks were adopted for model calibration using the same dataset of eighteen pre-classified drivers. Afterwards, WNN was used on a larger dataset, which consisted of 60 participants driving two types of vehicles in four major Chinese cities (Shi et al., 2017). Moreover, another extended study was implemented by Xu et al., which used PCMLP network on 72 samples collected with 18 drivers, 2 vehicles and 2 road types (Xu et al., 2015). The developed networks receive vehicle speed and speed change as input, and generate throttle position and brake pressure as output. The personalised models were then employed to follow the FTP-75 drive cycle to normalize the driving style variations. While no comparisons were made among the adopted neural networks, their capabilities of capturing the behavioural characteristics of those drivers were confirmed.

3.3.7 Stochastic models

Along with the machine learning based approaches, GMM and HMM were also used for driver modelling. Angkititrakul et al. (2011; 2012) developed two GMM-based models for car-following scenarios. Both studies focused on developing personalised models. While the first driver model was developed using solely GMM, the second model was a probabilistic combination of an individual model (DPM) and a general model (GMM). Both models were found to be capable of consistently improving the similarity to real human behaviour. Meanwhile, compared with the first and other traditional driver-adapt models, they found a notable improvement could be achieved with the second model as the incorporation of the general model can improve the robustness to unseen situations. However, it should be noted that the improvement might be caused by insufficient individual driving data. Therefore, its performance should be further assessed with more complete dataset containing all possible situations. Moreover, the influence of the incorporated general model on the personalization performance should also be evaluated to justify the proposed method.

Meanwhile, both Lefèvre et al. (2015a, 2015b) and Zeng and Wang (2017) developed a HMM-based model calibrated from the collected driving data. The model developed by Lefèvre et al. (2015a) used a combined HMM and GMR model to predict acceleration from training data, then MPC was incorporated to constrain safety violations. Personalised models of five drivers were established, with a satisfying result obtained through the comparison to the collected on-road driving data. Afterwards, they also developed a lane-keeping model that can predict unintentional lane departures based on the same mechanism (Lefèvre et al., 2015b). An interesting contribution of their models is the incorporation of the safety constrain model, which can override the previous control commands to ensure the vehicle's safety condition. However, the vehicle's acceleration was directly modelled as output instead of the pedal movement. Although this work was oriented to autonomous vehicles, modelling acceleration directly tends to neglect the dynamic behaviour of the vehicle system, especially for the engine component.

Meanwhile, Zeng and Wang (2017) simulated the relation between pedal movement and information of vehicle and road. Unlike those car-following models, this model was designed to predict the driver behaviour under free flow conditions. Another important feature of this study is the incorporation of road information, such as road speed limit and traffic signs. Evaluation experiments can be divided into two phases. Firstly, driving data of four human drivers were collected from a simulator to examine the model's prediction accuracy of drivers' next-step actions. Afterwards, this model was compared with three other models (constant, ARX and PID) to evaluate its prediction accuracy up to 60 steps. Although the prediction accuracy deteriorated in the long term, this model still outperformed the rest with a considerable margin.

3.3.8 Other data-driven models

Along with the models based on fuzzy logic and neural network, several other data-driven models were also developed based on various artificial intelligence approaches. Although these methods have much fewer applications, their validity and performance were still evaluated through respective examples. An interesting study was conducted by Chen et al. (2013), which attempted to model personalised driving style using DHG. This proposed method was a graph-based approach that had four levels of components. The first level contained the continuous raw data of nine driving factors collected from various sensors. Afterwards, significant changes in these data were captured to create nodes for each driving factor in the second level. Meanwhile, these nodes were connected using arcs corresponding to their time-order in the third level. The compositions of this level were assembled as a macro-node, which corresponds to a DRM and represents a driving behaviour. Finally, the macro-nodes were integrated to form the DHG of each driver. Using the collected real driving data, the performance of using DHG to model individual variations among different drivers was validated. Meanwhile, the involvement of lateral movement and overtaking scenarios also improve the competence of the proposed method. However, it should be noted that the lack of repeated experiments impairs the validity of this method. It would be worthy to formulate several DHGs of a same driver using data from different trips. The comparison among these DHGs can facilitate the evaluation of the stability and reliability of the proposed method.

Meanwhile, Demir and Çavuşoğlu (2012) developed a two-layer driver behaviour model based on HCSM. The first layer (DML) concerns tactical driving tasks, while the second layer (DIL) determines operational driving tasks. Through parameter modifications, they derived several driver models representing different driving styles. Afterwards, they applied these models to different vehicle types with random numbers, and created an urban traffic simulation. A satisfying realness was obtained through the evaluation with 30 participants. This study reveals the potential of incorporating driving style variations in the agent-based traffic simulation. However, it can be further improved if the models were calibrated using real driving data.

Another study was implemented by Jiang et al. (2018), which they developed a personalised longitudinal driver assistance system for car-following regimes. They first used MLIRL to estimate driving style parameters from the collected driving data. Afterwards, an IRL-based longitudinal assistance strategy was developed with the calibrated parameters. Their model was validated by comparing with human driving data. While no comparisons were made with other models and no evaluation on the training time, the potential of characterizing driver models from on-road driving data was validated.

Meanwhile, Rosenfeld et al. (2012; 2015) also developed a comprehensive model for personalised ACC. Using the ACAS field test data, they investigated the human preferences for ACC engage, disengage, and value selection using regression and discrete models. While individual variation was neglected, they found significant difference among the predefined three driving style groups. This phenomenon confirmed the necessity of developing such systems. Moreover, they found the inclusion of drivers' demographic information could effectively increase the prediction accuracy by approximately 24%, reaching 70% for the discrete model and 0.78 for the regression model.

3.4 Discussion

3.4.1 Analysis of selected input variables

Along with the detailed analysis of located studies, the selected input parameters of these models were also compared and evaluated to facilitate following research. With the ultimate aim of building driver models that can simulate human driving style, the selection of appropriate input parameters is vital to the model's performance. Therefore, selected parameters should have high correlations with the underlying driving style, and are capable of revealing the variations of different styles. The selected input parameters of located studies are listed in table 3.3. It should be noted that six studies have not clarified their adopted input variables, which reduces the number of listed studies to 42.

Table 3.3. Selected input parameters of the identified studies

Authors \ Inputs	Jerk	Speed	Position	Weather	Road type	Speed limit	Pedal force	Road grade	Speed error	Acceleration	Road surface	Speed change	Pedal position	Steering angle	Desired speed	Relative speed	Road curvature	Distance to stop	Time to collision	Driver attribution	Lateral deviation	Distance change	Lead acceleration	Headway distance
Shi et al. (4)		X							X															
Bolduc et al.		X																						X
Hellström&Jankovic									X						X									
Shirazi & Rad																	X				X			
Su et al.																X								X
Macadam et al.																X								X
Angkititrakul et al.		X																						X
Javanmardi et al.						X		X	X															
Bifulco et al.		X														X								X
Kamal et al.		X														X								X
Kesting et al.		X														X								X
Bifulco et al.		X														X								X
Zhai et al.		X														X								X
Yu et al. (5)		X														X								X
Shakouri et al.		X														X								X
Tang et al. (a)		X														X								X
He et al.		X														X								X
Zalila & Lezy												X				X						X		
Lefèvre et al. (a)		X	X													X								X
Tang et al. (b)		X														X				X				X
Khodayari et al. (2)		X														X				X				X
Ossen et al.		X				X										X								X
Zhang et al.																X				X			X	X
Angkititrakul et al.		X					X																	X
Wang & Liaw		X															X				X			X
Luo et al.	X	X								X						X								X

Zeng & Wang		X				X				X			X					X						
Jiang et al.		X														X			X				X	X
Hao et al.		X								X						X							X	X
Lefèvre et al. (b)		X	X							X				X		X								X
Geng et al.		X		X		X		X			X						X							
Rosenfeld et al. (2)					X											X				X				X
Chen et al.		X	X							X			X	X										

As shown in table 3.3, the speed of the host vehicle, the relative speed between the host and its preceding vehicle, and the headway distance are the most commonly used parameters in the identified driver modelling studies, with accumulated numbers to be 33, 28, and 31 respectively. It can be noted that a sum of 14 studies adopted these three parameters as complete inputs. Meanwhile, they were also combined with additional variables in another 9 studies. Moreover, it was found that the majority of these studies were aiming to develop numerical models for car-following behaviours. This phenomenon may partially because these three parameters are essential to the driver's cognition and can effectively reveal the potential variations between different driving styles.

Along with these numerical studies, a subset of those three parameters (relative speed and headway distance) was adopted by Macadam et al. (1998) in their neural network based model, while all three were used by the driver model developed by Bifulco et al. (2008). Meanwhile, the series ANN studies of Shi et al. (2014; 2015; 2017) and Xu et al. (2015) all used speed and speed error as the models' inputs. It should be noted that both parameters have been extensively used for PID based studies that attempt to follow or reproduce a predefined speed profile (Chatzikomis and Spentzas, 2009; Filev et al., 2009). A common criticism of driver models developed using these two parameters is the insufficiency of imitating human behaviours (James et al., 2004). Meanwhile, while more road-related parameters were considered by Geng et al. (2016), their ANN focused on turning events only, and was not capable of replicating car-following behaviours.

Moreover, among the studies that developed upon fuzzy logic, the same three parameters were only utilised in the study conducted by Kamal et al. (2008). Meanwhile, Su et al. (2018) used a subset of the above parameters, which consisted of relative speed and headway distance only. Moreover, Zalila and Lezy (1994) adopted speed change and distance change as replacements of speed and headway distance, in order to achieve personalised cruising control. In addition to those three parameters, those two models developed by Khodayari et al. (2011, 2013) also incorporated driver reaction delay as an additional input, to model the humanized difference of the time between stimulus and reaction. Meanwhile, Hao et al. (2016) considered more parameters related to the leading vehicle, such as the speed and acceleration of the leading vehicle. Along with these car-following models, Wang and Liaw (2014) adopted the same parameters as Su et al. (2018) for longitudinal control, while incorporating lateral deviation and road curvature to determine lateral movement strategy.

The stochastic models developed by Lefèvre et al. (2015a, 2015b) both used all the three parameters, and incorporated some additional parameters (position for the ACC model; acceleration and steering angle for the LKA model). Meanwhile, Angkititrakul et al. (2012) also adopted a subset of the three parameters, e.g. speed and headway distance. However, input parameters of the remaining two studies vary significantly from the above research. Instead of treating driver and vehicle as a complete unit, both studies considered pedal measurements as an important input factor, as Angkititrakul et al. (2011) incorporated pedal forces and Zeng and Wang (2017) adopted pedal positions. It should be noted that the incorporation of pedal measurements requires a detailed and accurate vehicle model. While it introduces additional requirements and increases the complexity of simulation, using pedal movements as the model’s output can significantly improve the similarity to human behaviours, and can hence better reveal the individual variations of driving style.

Along with those studies that developed upon similar methods, the input parameters of other separate studies are rather distinct. It should be noted that the model developed by Chen et al. (2013) had the largest number of inputs. While acceleration, speed, and position in both lateral and longitudinal directions were considered, additional parameters, such as steering angle and both pedal positions were also incorporated, resulting in a sum of 9 parameters. The inclusion of all these parameters is not realistic for models based on ANN and fuzzy logic, as the rise in measurement's dimension can exponentially increase the complexity of the training of ANN and the formulation of fuzzy controllers. Therefore, the practical usage of these additional parameters is restricted in many data-driven methods.

Meanwhile, another study worth noting is the model developed by Rosenfeld et al. (2012; 2015). As shown in table 3.3, their model is the only instance that adopted some human factors as input parameters. While the exact influence was not evaluated, the inclusion of gender, age, and income level can improve the understanding of the driver's psychology motivations of certain driving behaviours. However, as inner factors, the impacts of these variables are more difficult to model from the collected driving data. Therefore, they may not be suitable for developing data-driven models.

From the above analysis, it can be noted that variables such as speed, relative speed, headway distance, and pedal positions should be adopted for modelling longitudinal control, while steering angle, road curvature, and lateral position should be considered for developing lateral movement strategy. Meanwhile, although treating driver and vehicle as a complete unit and using either vehicle speed or acceleration as output can reduce the complexity of the model, adopting driver-related parameters, such as pedal positions, gear selection, and steering angle as the model's output prevail in mimicking human driving behaviours. Moreover, using these human-related variables can also facilitate the model's integration with real vehicles, which can improve the practical significance of developing such driver models.

3.4.2 Analysis of adopted modelling methods

As listed in the previous section, it can be noted that although the adopted modelling methods vary among these studies, they can be generally classified into two major groups, namely numerical and data-driven. Meanwhile, each major group can be further divided into three (FVD, MPC, and other) and four subgroups (fuzzy logic, ANN, stochastic, and other), respectively.

Among the first major group that using numerical models, it can be noted that the movement of the following vehicle is defined as a mathematical function of headway distance, relative speed, and host speed in the majority of studies. Meanwhile, the driving style variations are often described in some pre-determined indexes or coefficients. The major advantage of these numerical models is their efficiency in computation, which enables them to be easily incorporated in traffic flow simulation, especially with a large number of vehicles. Therefore, these models have been widely adopted in microscopic and macroscopic traffic simulation studies (Tang et al., 2014; Zhang et al., 2017). However, it should be noted that although the driving style parameters in some studies were calibrated from real driving data, these models' performance in mimicking human driving styles still lack of evaluation. As human reasoning are a process consisting of uncountable mysterious factors (Cziko, 1989), using several driving style parameters in a mathematical function will hence restrain the ability to simulate real human behaviours. Therefore, it can be noted that while these numerical models can reveal driving style variations to some extent, the potential of capturing complete humanized driving attributions is restricted by the limited possibilities for calibration.

Meanwhile, the second major group consists of more data-driven models. The underlying relations between the driver's output and perceived input are treated as a black box. Therefore, different machine learning and stochastic-based approaches have been adopted to simulate these relations. All these models attempted to decipher the inner relations between human driver's cognition and action from the real driving data, collected from either on-road instrumented vehicles or driving simulators. Compared with those numerical models, one major advantage of these approaches is the improved performance in simulating humanized behaviours. Moreover, they can also adopt more humanized input and output parameters than the numerical models, such as pedal positions and steering angle. It should be noted that instead of treating driver and vehicle as a complete unit, these data-driven models showed a higher tendency of differentiating between both, and are hence more similar to human driving behaviours. While the advantages of data-driven models are obvious, they also suffer from some major drawbacks, most notably is the expensive computation requirements. Owing to the relative more complex architecture of these algorithms, the simulations with these models always have higher requirements on the hardware platform. Moreover, large amounts of real driving data are also required by these models for training and inferring purpose. Therefore, these data-driven models are more commonly used in simulating microscopic traffic scenarios with a limited number of vehicles.

Along with similar general features of these data-driven models, the adopted different algorithms also have respective merits and drawbacks, as listed in table 3.4. It can be noted that compared with the fourth group, learning performances of the first three algorithms are more recognized and accepted with multiple instances. As these algorithms are more commonly adopted in similar research, their validities are hence more convincing and trustworthy.

Meanwhile, it should be noted that the performances of stochastic algorithms are highly depended on the integrity of the collected dataset. Therefore, both fuzzy logic and neural network based models are more preferable as they have higher inferential capabilities, and are more robust to the deficiencies in dataset.

Owing to the training process of neural network, its major advantage is the potential to achieve the best performance in characterizing the individual driving pattern from the collected data. Meanwhile, the training process also causes its major drawbacks, as this process is always time-consuming and has a high risk of overfitting. Moreover, it is also difficult to determine a proper structure of the neural network. Therefore, sufficient optimisations are needed for neural network to achieve a satisfying performance in emulating human driving behaviours.

Table 3.4. Evaluation of different data-driven algorithms

Algorithm	Advantage	Disadvantage
Fuzzy logic	• similar to human reasoning • robust to incomplete data • high interpretability • high tolerance to less accurate traffic estimations	• require optimisations • limit on number of variables • difficult to define the rules • difficult to define the membership functions
Neural network	• mimic human brain • robust to incomplete data • high fault tolerance • can contain large number of variables	• require for training • hardware dependence • unexplained behaviour • difficult to determine the structure
Stochastic	• high flexibility • high efficiency in learning	• less robust to incomplete data
Others	• inspiring applications with different algorithms • incorporate many different combinations of variables	• lack of repetitive research using similar approach • algorithms need more evaluation and validation

Meanwhile, fuzzy logic prevails in mimicking the process of human reasoning. As human drivers' perception about the traffic environment is based on inaccurate estimation, incorporating vagueness in the driver model can hence maximize the similarity of this feature. Meanwhile, fuzzy logic controllers are often more computational efficient than neural network based models. However, it should be noted that the determination of fuzzy rules and membership functions of each variable remain controversy, with no consensus on a unified approach. Therefore, a fuzzy logic controller with properly defined fuzzy rules and membership functions is vital to the performance of the established driver models.

3.5 Chapter summary and conclusions

This literature review aims to evaluate the existing studies on different driver modelling approaches that addressed the human factors. The process of a systematic literature review is followed to ensure this review is replicable, transparent, and explicit. Four sets of keywords that correspond to the aim of this review were first defined as the research pillars to set literature search criteria. Afterwards, three different combinations of these four pillars were constructed to formulate the search strings, which were then used to locate relevant articles in six electronic databases. After excluding duplicates and adding relevant papers using the snowball approach, a total of 48 articles was located in the final selection.

After locating the relevant papers, a preliminary analysis was implemented first to provide a descriptive outline of these studies. A growing research interest in this emergent field was confirmed with the increasing publication rate in recent years. Meanwhile, the variety of publication sources also indicated that driving style modelling is a new topic, as no specialised journals or conferences were found.

Along with the preliminary analysis, a more detailed analysis was also implemented. These located studies can be roughly divided into two major groups based on their adopted approaches, namely numerical and artificial intelligence. Three sub-groups were also derived from numerical models, which are FVD, MPC, and others. Meanwhile, four types of model based on artificial intelligence were identified as fuzzy logic, neural network, stochastic, and others. The major advantage of those numerical models is the high computation efficiency, which allows them to be easily integrated in microscopic and macroscopic traffic simulations. However, while the driving style variations can be revealed through some predefined parameters in these models, their performance in mimicking human driving styles still requires more thorough evaluations. This is mainly caused by the restricted calibration possibilities in the formulation of these numerical models. Meanwhile, the models of the second group are more data-driven. These models attempted to infer the underlying relations between deriver's actions and perceived inputs from their own driving data. These models prevail in the potential and performance of simulating human driving behaviours, and allow the incorporation of more humanized control parameters, such as pedal positions and steering angle. However, a major drawback of these models is the computation complexity. Therefore, they are more commonly used in microscopic simulations. Moreover, a sufficient and complete collection of real driving data is also essential for developing these models to ensure the validity of the calibration process.

Along with modelling methods, the selected input parameters of these studies were also evaluated. Among those 42 studies with clarified input parameters, it can be noted that three particular parameters have the highest frequency, which are the speed of the host vehicle, the relative speed between the host and its preceding vehicle, and the headway distance. Owing to their relevance to the driver's cognition characteristics, these three parameters and the subsets of them have been extensively used in both numerical and artificial intelligence based models that focus on car-following behaviours. Moreover, pedal position is another important parameter when treating driver and vehicle as separate units. In addition to these parameters that concerned longitudinal control, steering angle, road curvature, and lateral position are commonly used when considering lateral movement strategy. While there has been no consensus on the selection of these parameters, it can be noted that the incorporation of these human-related variables can improve the model's performance in mimicking human driving behaviours, and hence facilitate the integration with real vehicles.

While the existing studies on humanized driver modelling are rather limited, it should be noted that the potential benefits of developing such driver models are promising. Firstly, these models can be incorporated with ADAS and the control strategy of autonomous vehicles. As these humanized driver models are capable of replicating personalised driving styles, this incorporation can hence increase the similarity between these auto-pilot systems and corresponding human drivers. This bonus feature can potentially increase the customers' approval and acceptance of these systems, as it can reduce the deviations of vehicle manoeuvre from human drivers. Secondly, these models can be used to develop personalised eco-driving assistance devices. This is because these models can be personalised to predict the driver's future control actions with high confidence. After adapting eco-driving style to these models, the generated driving advice can be personalised to address the driver's intention, while maintaining a more eco-friendly driving manoeuvre. Thirdly, these models can also benefit traffic simulation studies. Assigning different driving styles to simulated traffic can increase the realness of traffic modelling, and introduce some bonus features to traffic simulation, such as evaluating the influence of different driving styles on traffic congestion, etc.

With the outlined three major benefits of developing humanized driver models, it can be noted that more research efforts should be devoted to this emergent research area. Three promising aspects are hence identified that should advance the current research in this area. Firstly, as there are currently no consensus on the selection of the modelling parameters, a more thorough justification and evaluation of this selection should hence be conducted to improve the model's similarity to human drivers. Secondly, while there have been seven different approaches to develop these humanized driver models, their performance have not been evaluated using a same dataset. Therefore, some cross-comparison studies should be implemented to further assess the suitability of these approaches. Thirdly, although some of these models are calibrated from real driving data, their capabilities of replicating human drivers are still lack of evaluation. Therefore, an enhanced approach for evaluating these driver models should be developed to further improve the credibility of these studies.

Chapter 4 – *Methodology*

This chapter presents the theory foundations of the adopted methods in this study. It consists of five subsections, namely real world data collection, driving data processing, driving style classification, driver modelling and calibration, and simulation environment.

Parts of each sub-section in this chapter have been separately published in several sources. While the first sub-section corresponds to a paper presented at the SAE Intelligent and Connected Vehicles Symposium, the second sub-section was presented at the IEEE International Conference on Intelligent Transportation Engineering, and published in both the conference proceedings and the International Journal of Machine Learning and Computing. Meanwhile, the final sub-section was published in the proceedings of the International Conference on Applied Human Factors and Ergonomics and included in a submission to IEEE Transactions on Intelligent Transportation Systems.

4.1 Introduction

From the flowchart shown in figure 4.1, it can be noted that the main contents of this chapter have been divided into five sections.

The real driving data collection is introduced first in section 4.2. It mainly involves the instrumentation of the vehicle, the test route selection, and driving data storage. The real driving data were collected from three separate sources, which are the long-range radar sensor, the dashcam, and the vehicle's ECU information retrieved from the OBD-II port.

With these collected raw data, the data processing is presented in section 4.3. The post-processing of ECU information, the interpretation of the radar measurements, the headway distance estimation from camera footage, and the Kalman filter optimisation are all included in this section. The processed dataset consists of the synchronised headway distance, vehicle speed, engine speed, pedal position, and gear selection information.

These data were then supplied to the driving style classification approach, detailed in section 4.4. This section first introduces the event detection approach. Afterwards, the feature parameter selection based on DWT and PCA are presented. Finally, the theory foundation of the proposed classification approach, SVC, is included. Driving styles of different participants were classified using this proposed approach.

Section 4.5 details the driver modelling approach. As discussed in section 3.4.2, fuzzy logic has been adopted to develop the driver models. Therefore, this section presents two fuzzy logic calibration methods. The processed driving data from section 4.3 and the classified driving style from section 4.4 were adopted to develop the driver models, which can interact with the vehicle model and the simulation environment proposed in section 4.6 to validate and assess the influence of driving style on fuel consumption.

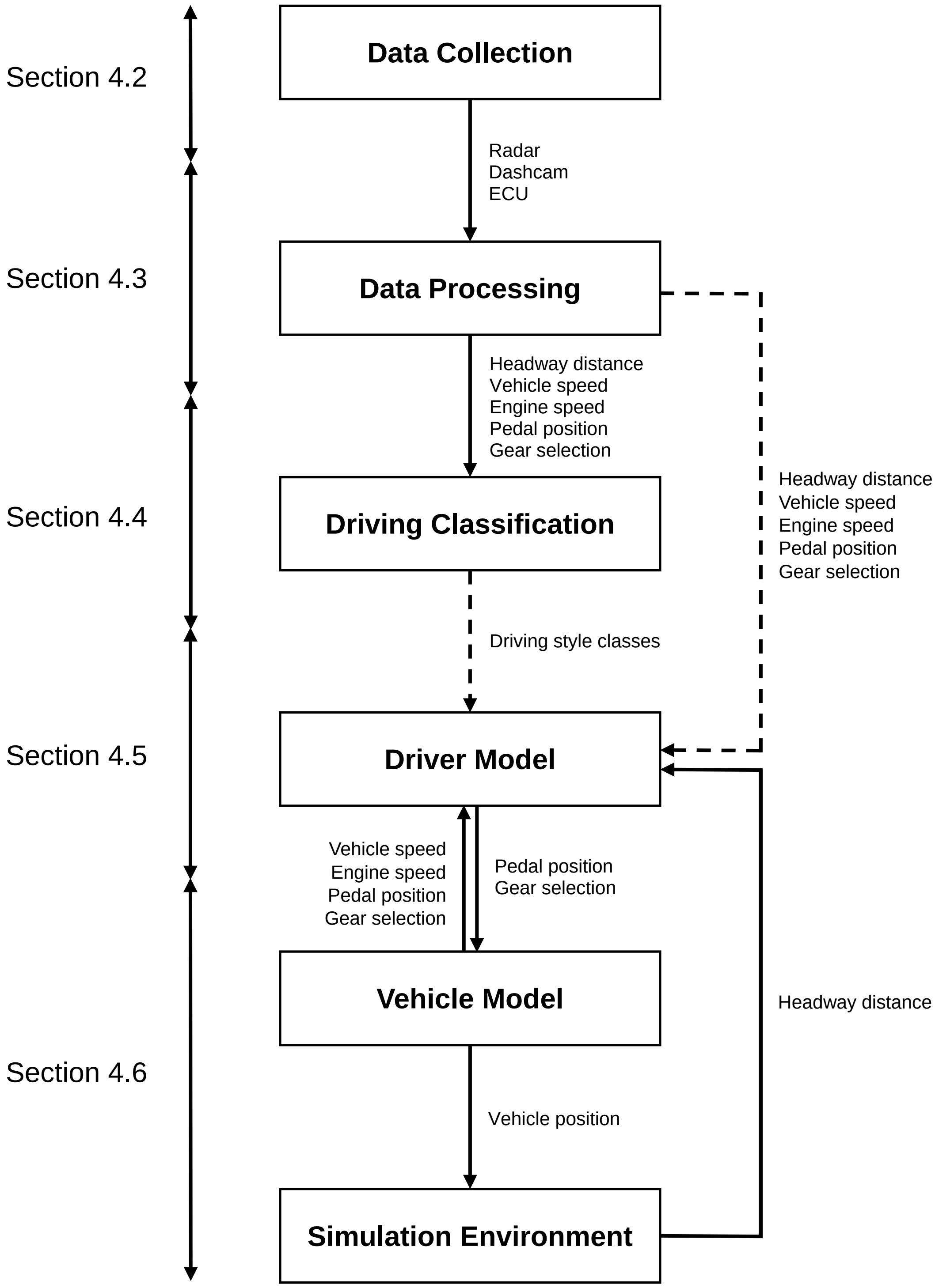


Figure 4.1. Method flowchart

4.2 Real driving data collection

4.2.1 Introduction

As outlined in the previous section, data-driven driver models can potentially achieve a better performance in mimicking human driving styles. Therefore, this thesis proposes to develop fuzzy logic-based data-driven driver models to facilitate the investigations into the correlations between different driving styles and fuel consumption. As an essential preliminary step of developing data-driven models, sufficient real world driving data need to be collected in advance to facilitate the driver modelling and hence maximize the model's similarity to human drivers. Theoretically, the collected driving data should consist of all aspects of driving, involving but not limited to different weather conditions, various road types and structures, all driving scenarios, etc. Meanwhile, all parameters related to driving conditions and can affect drivers' decisions should also been gathered, such as information on the vehicle state, traffic condition, road infrastructure, and even drivers' physical attributes and mood. The integrity of the collected driving data can have a huge influence on the accuracy and performance of the established driver models. However, owing to the limitations of related equipment, it should be noted that collecting extensive and complete driving data is not realistic in practical. Thus, only the most prominent factors have been considered for the data collection phase.

From drivers' perception, two types of driving-related information with most significance on driving behaviours were identified as vehicle state information and traffic scenarios. As outlined in the previous section, typical vehicle state information mainly consist of vehicle speed, engine rpm, gear selection, and pedal positions. Meanwhile, traffic scenarios mainly include the relative speed and headway distance between the host and its preceding vehicle in car-following regimes. Based on the review of relevant studies for driver modelling in the previous section, it can be noted that these variables can effectively reveal the driving style difference at both cognition and action levels, and are hence sufficient for developing the driver model proposed in this study.

In order to collect demanded driving data, four commonly used approaches in behaviour recording studies are identified as in-vehicle observation, site-based traffic observation, driving simulator, and instrumented vehicle (Sagberg et al., 2015). While the first two methods are simpler to implement, which mainly require the involvement of either human observers (Tillmann and Hobbs, 1949; Rathmayer et al., 1999; Hjälmdahl and Várhelyi, 2004) or cameras (Keskinen et al., 1998), they tend to be more subjective and cannot collect the demanded type of data for driver modelling.

Meanwhile, both driving simulator (Desai and Haque, 2006; Reed, 2010) and instrumented vehicle (Reimer et al., 2013; Takeda et al., 2011) can be used to collect more accurate and objective driving-related data with the assistance of external hardware. The major benefit of driving simulator is the high repeatability of traffic scenarios under more controlled laboratory environment. Therefore, they have been extensively used in driver training and comparative studies (Reed, 2010; Beloufa et al., 2012). However, as the complexity of these simulators can vary significantly, the realness of these simulators is difficult to evaluate. Some potential deficiencies of the simulator itself can introduce huge biases into the experiments and hence impair the integrity of the results.

Compared with the above three methods, the instrumented vehicle is the most disruptive behaviour recording approach. External data collection equipment has to be mounted inside the vehicle. Typical devices are identified as CAN bus loggers, data storage devices, cameras, and sometimes microphones as well. These devices are not hidden, thus drivers know their behaviours are being recorded, which is a main argument about the veracity of this approach. Nevertheless, owing to the involvement of actual vehicle and traffic interactions, the instrumented vehicle is still closer to naturalistic driving compared to the other three approaches (Sagberg et al., 2015). Therefore, this method was adopted for the collection of real world driving data.

4.2.2 The instrumented vehicle

In order to collect demanded real driving data, a vehicle should be properly instrumented with essential equipment first. Therefore, considering the availability of relevant test vehicles, a 2014 VW Sharan was selected as the base vehicle for this study. A detailed specification of this vehicle is listed in table 4.1.

Table 4.1. Specifications of Sharan (Parkers, 2010)

Specification	**Volkswagen Sharan 2.0 TDI CR BlueMotion 5d**
Performance	
Power	138 bhp
Top speed	121 mph
Torque	320 Nm
Engine	
Engine size	1968 cc
Cylinders	4
Fuel type	Diesel
Transmission	
Gear ratio 1	3.92 : 1
Gear ratio 2	2.05 : 1
Gear ratio 3	1.75 : 1
Gear ratio 4	1.23 : 1
Gear ratio 5	0.94 : 1
Gear ratio 6	0.77 : 1
Dimension	
Weight	1699 kg
Length	4854 mm
Width	2081 mm
Height	1720 mm
Tire size	225/50 R17

Along with the base vehicle, external devices need to be mounted to collect the demanded vehicle state and traffic scenario information. Therefore, an Influx Rebel CT data logger (shown in figure 4.2) was adopted to retrieve and record live information from the vehicle's ECU through the OBD-II port. This compact data logger provides four CAN connection ports with a maximum transmission rate of 1000 kbps. Through repeatedly sending the predefined

OBD-II PIDs to the vehicle's ECU, relevant vehicle state parameters, such as vehicle speed, engine speed, throttle pedal position, and instantaneous fuel consumption, can be obtained and recorded by the data logger at a fixed frequency.

Figure 4.2. Influx Rebel CT data logger (Influx, 2018)

Table 4.2. Comparison between sensors

Sensor	Benefits	Drawbacks
LIDAR	Immune to light condition	Need to mount outside
	High accuracy	Expensive price
	Max range around 200 m	Sensitive to snow, fog, rain and dust
Radar	Immune to weather and light	Difficult to distinguish targets
	Max range around 200m	Hard to detect pedestrians
	Reasonable price	Narrow field of view
Camera	Cheap	Sensitive to light
	Detect colour	Computational expensive
	Recognize signs	Low precision
Ultrasonic	Lowest price	Short measurement range

Unlike the vehicle state information, which can be directly retrieved from the vehicle's ECU, the traffic scenario information can only be obtained from external object detection sensors. Similar to the application of autonomous vehicles, some common sensors with this functionality were identified as LIDAR, radar, camera, and ultrasonic sensor. While these sensors are capable of measuring the demanded headway distance, they have corresponding benefits and drawbacks, as listed in table 4.2.

It can be noted from the above table that although LIDAR can obtain a general better performance, its price is a major crisis in practical applications. Meanwhile, ultrasonic sensors have very limited measurement range, and are not suitable for headway distance measurement. Compared with these two sensors, radar is a more affordable option with satisfying performance. It is more compact design and robust to various weather conditions. Some 77 GHz radars can also measure up to 200 m, which is important in driver modelling, especially in highway scenarios. Meanwhile, radar has been widely adopted in the automobile industry, mainly for adaptive cruise control and collision avoidance. For instance, Audi “Pre sense” system, BMW “Driving Assistant Plus” system and Mazda’s “Smart Brake Support”. Aside from these industrial applications, there have also been some studies using radar as a range finder, mainly in autonomous driving research. For example, Wei et al. (2013) used six radars, together with other sensors, to develop an autonomous vehicle with minimal appearance modifications. Meanwhile, Göhring et al. (2011) fused a long-range TRW radar and several LIDARs to enable autonomous following behaviour on highways.

Inspired by the satisfying performance in relevant studies (Wei et al., 2013; Göhring et al., 2011), a 77 GHz radar was hence procured for headway distance measurement. After a detailed comparison among products developed by various manufacturers, namely Delphi, Bosch, Sick and Continental, the Continental ARS 308-2C long-range radar was selected considering the trade-offs between performance and budget. As shown in figure 4.3, this radar has a high speed 1 CAN interface with the maximum transmission rate of 500 kbit/s, with a measurement update frequency of about 15 Hz. The dimension of this device is 120 mm×90 mm×46 mm and weighs less than 500 g. It requires a 12 V DC power supply and can hence be driven by the in-vehicle power plug.

Figure 4.3. Continental ARS 308-2C radar (Continental, 2009)

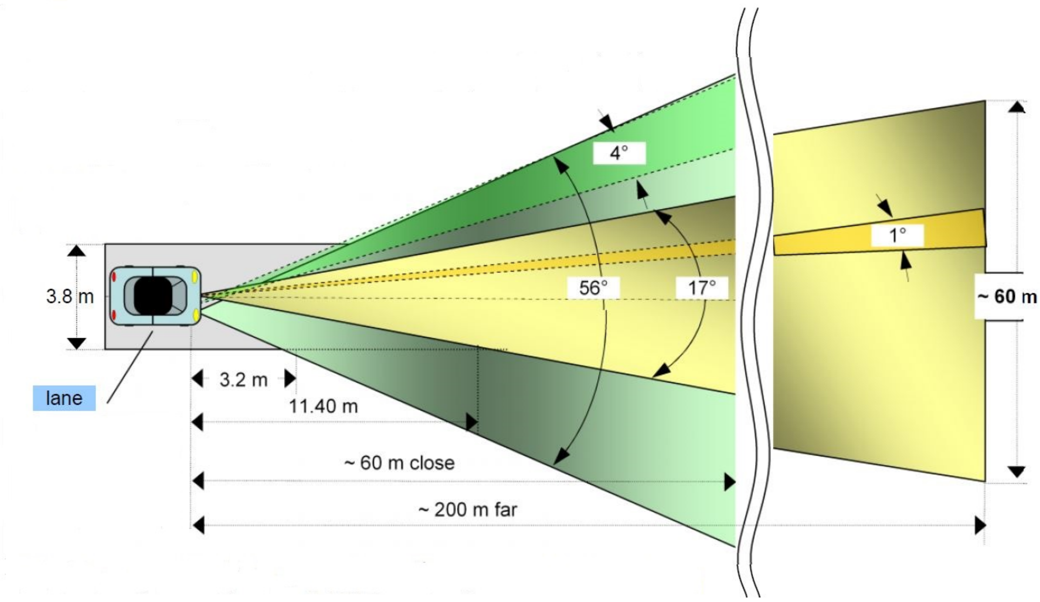


Figure 4.4. Radar measurement range (Continental, 2009)

The measurement range of this radar is illustrated in figure 4.4, which consists of a narrower zone of up to 200 m with a FOV of 17° and a wider zone of up to 60 m with 56°. This radar provides an object-tracking mode, which can detect up to 40 objects in each measurement cycle, and keep tracking them until vanished. Typical output in this mode is object id, longitudinal distance, lateral distance, the object's longitudinal speed and acceleration, and its dimension. All these outputs can be integrated as a 64 bit CAN message and published on the CAN bus with a predefined structure (start bit and length). Therefore, after modifying the configure file of the Rebel logger accordingly, the output from the radar can hence be recorded by the logger at a fixed frequency.

Along with the Continental radar, a Nextbase 512G dash cam (shown in figure 4.5) was also installed on the vehicle for headway measurement. As radar measurements can be messy and difficult to interpret, utilising a dash cam to record the corresponding traffic scenarios can facilitate the analysis of radar measurements. Moreover, it can also provide an additional source of headway information for performing sensor fusion to compensate the potential drawbacks of using an individual sensor. This dash cam has a 6G lens with an aperture of F1.6 and can provide a 140° FOV. It can record high resolution1080p videos at 30 fps. All recorded files are stored in an external SD card for post-processing. Meanwhile, the dash cam can also be powered by the in-vehicle power plug.

Figure 4.5. Nextbase 512G dash cam (Nextbase, 2015)

Figure 4.6. The instrumented vehicle

During the instrumentation of these devices, the data logger was secured under the backseat and connected to the vehicle’s OBD port using an extended convert cable, while the dash cam was securely adhered to the windscreen facing forward to record leading traffic. Meanwhile, in order to optimise the performance of the radar, additional bracket and protection cover were manufactured and the radar was mounted behind the bumper, located near to the centre of the vehicle front. The architecture of the instrumented vehicle is illustrated in figure 4.6.

4.2.3 The test route

Along with the instrumented vehicle, a test route was designed for driving data collection. In order to ensure the gathered data is sufficient for driver modelling, the proposed test route should consist of all common road types, and the collection phase should be long enough. Therefore, after liaising with related parties, and balancing between other projects, a shared communal route was selected for a data collection phase of three consecutive months. The adopted route was illustrated in figure 4.7, which starts from the University of Bath and ends near Salisbury. A total of 90 trips were recorded, with each trip to be approximately 45 miles and lasting about 63 minutes.

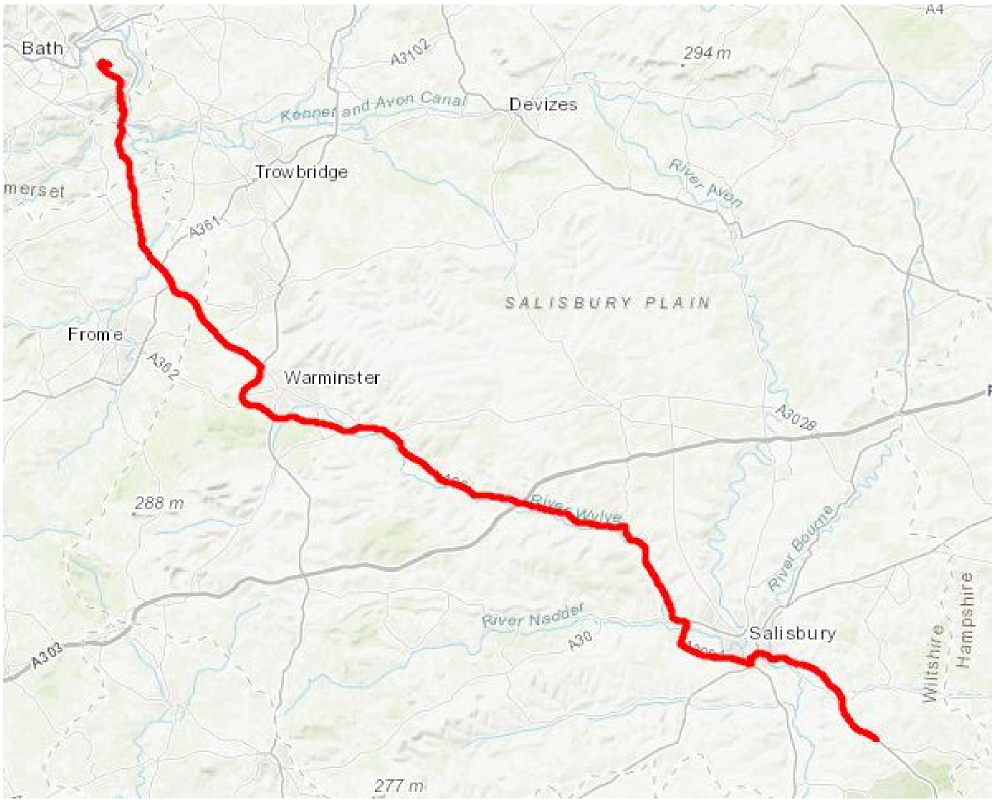


Figure 4.7. Route for data collection

The selected route has a mixed road segments, consisting of three typical road types, namely urban, rural, and highway. While rural segment occupies a dominant proportion, the other two road types are also involved. Meanwhile, the maximum vehicle speed during each trip is approximately 100 km/h.

It should be noted that although the driver modelling can still benefit from more collected real driving data, continuing data collection is unnecessary considering the trade-offs between the demanded efforts and benefits, especially the availability of human participants and related equipment. This is mainly because during the three months data collection phase, a large scale of real driving data has already been collected on the same road infrastructure, under various weather conditions, and at similar time of the day. Extensive traffic conditions were also covered during this period. As the driving style proposed in this study is more like a habitual choice of driving manoeuvres, the collected driving data is hence considered sufficient to reveal this general tendency. Therefore, the driving data collection phase only lasts three months, and the collected data should be sufficient to develop the personalised driver models for this study.

4.2.4 Driving data storage

During the three months of data collection phase, both the Rebel data logger and the dashcam were equipped with an SD card to directly record and store live information. Afterwards, the logged vehicle state information and radar raw measurements were downloaded from the Rebel logger as a .ivd type of file at a weekly manner. Meanwhile, owing to the relatively large file size of the recorded camera footage, these .mov videos were downloaded daily to ensure there is sufficient space on the SD card for new recordings.

Figure 4.8. Western Digital My Book Duo

The accumulated size of the Rebel logger files is approximately 29.7 GB, while the stored video footage is over 1.9 TB. After downloading from the SD card daily, the collected raw driving data were then uploaded to the university's server for storage purpose. Meanwhile, in order to ensure the safety of the collected data, an 8 TB Western Digital My Book Duo (shown in figure 4.8) with data mirror function was also purchased as a backup option. This external hard drive has two RAIDs, and was configured to the mirror mode, which can still ensure the data safety even when one RAID stops working. With these two storage backups, the collected driving data can hence be secured.

4.3 Driving data processing

4.3.1 Rebel logger data processing

After the raw data were collected and securely stored, they were then processed to facilitate following research.

While both the vehicle state information and radar measurements were recorded with the Rebel logger, the former can be easily decoded and converted into excel files using the Influx provided software “DiaLog” at a fixed frequency of 2 Hz. However, owing to the restriction of decoding frequency in this software, the raw radar measurements cannot be fully converted. Therefore, the raw radar measurements were directly outputted as excel files, and an external decoding software should be developed to extract useful information from recorded raw CAN bus messages.

Owing to its excellent performance in compiling and computation speed, Python was selected as the programming language for developing the proposed software. In order to ensure the developed software is user-friendly and easy to use, a GUI-based architecture was hence established. Thanks to the open source feature of Python, there have been several different toolkits developed to facilitate GUI applications, most notably, Tkinter, wxPython, QT, and GTK. While each toolkit has its relative advantages and drawbacks, wxPython based on Python2 was selected to develop the proposed GUI.

Mainly developed by Dunn and Pasanen in 1998, wxPython is the wrapper of wxWidgets in Python language (Precord, 2010). It is currently implemented as a Python extension module, which consists of several predefined widget classes, such as wx.Button, wx.StaticText, and wx.TextCtrl. Using these widgets, a top-level GUI was developed first. Afterwards, corresponding functions were programmed and linked with those buttons to fulfil the demand functionality of this GUI, which was then complied as an independent interface.

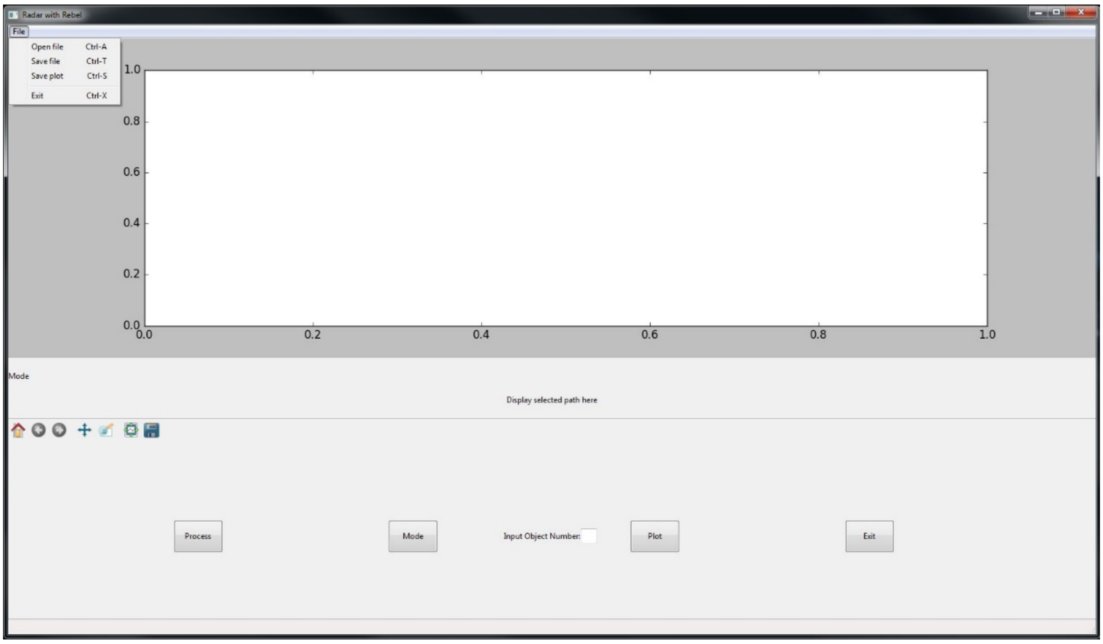


Figure 4.9. Screenshot of the developed GUI for radar analysis

A screenshot of the developed GUI is shown in figure 4.9. It can be noted that there are three file options and four control buttons, along with six plot manipulators and one input space to specify the object number. The processing of radar data should follow a default procedure. Firstly, the “Open file” option should be clicked to select the excel file of raw radar measurements from the popped up folder navigator. Afterwards, the “Process” button should be pressed to start processing the raw CAN messages and decode the information based on the predefined message structure. During the processing, the user will be notified the current progress and alerted when finished. Afterwards, the object ID of interest should be typed into the text space provided. Then the “Plot” button needs to be pressed to generate the plot of the specified object in the provided figure zone. The plotted figure can be viewed using those six plot manipulators, each responsible for zoom out, move left and right, move in any direction, zoom in, select, and save, respectively. Meanwhile, the “Save plot” option can also be used to output the figure as a .jpg file. In order to facilitate following applications, the “Save file” option can be used to save the processed radar measurements and output them in a .csv file. Moreover, there are also a button and a file option for abort and exit this radar measurement processing tool. This complied Python-based processing tool can achieve significant faster speed than a counterpart developed in Matlab. When processing a same raw data file simultaneously using both tools, this Python-based tool can be over twice faster than the corresponding Matlab-based programs. Therefore, this complied tool was adopted to process all raw radar data to extract demanded traffic related measurements.

4.3.2 Camera footage processing

Along with the Rebel data and radar measurements, the dashcam footage was also processed to function as an additional source of headway distance measurements. The incorporation of another source of sensory measurements can compensate the potential drawbacks of using an individual sensor. Consistent improvements through performing such sensor fusion have been confirmed in multiple studies (Schlegl, 2010; Filonenko, 2015). Moreover, during processing the radar data, some deficiencies of the radar measurements were found. For instance, it can be difficult to isolate the desired target from all the measured objects directly from the radar measurements. Meanwhile, the radar data can be inconsistent, and the desired target can be missing in some measurement cycles. Owing to these deficiencies of using radar alone, the camera data were hence processed to provide an additional source of headway distance measurements.

In order to retrieve headway distance information from the recorded dashcam footage, the transformation matrix between 3D world frame and 2D image frame needs to be established prior to other manipulations. This is also called IPM. In order to formulate this coordinate conversion, an intermediate 3D camera coordinate frame needs to be introduced.

The relations between three coordinate frames are illustrated in figure 4.10. The parameters for conversion between camera and image coordinate frames are intrinsic parameters, such as focal lengths and optical centres. Meanwhile, the transformation between the world and camera coordinate frames is defined by extrinsic parameters, such as the camera's height, pitch and yaw angles.

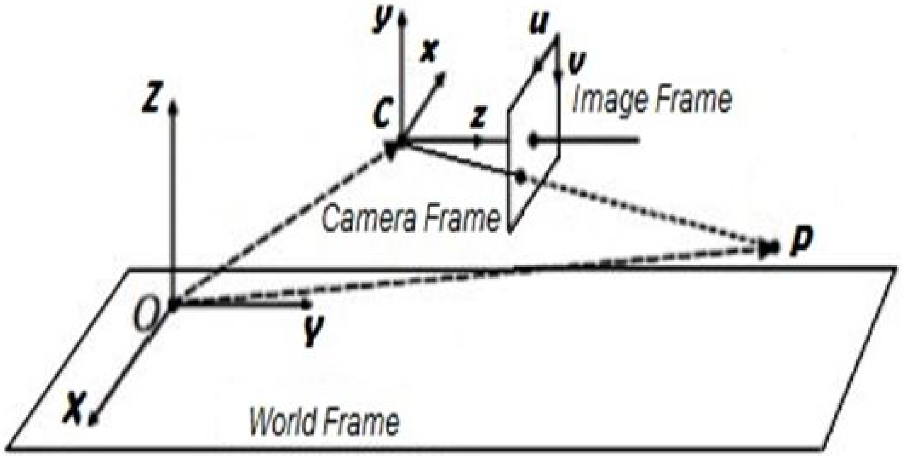


Figure 4.10. Relation between three coordinate frames

As the intrinsic parameters of each camera are fixed after manufacture, they should be investigated as the first step of image processing. As indicated by Zhang (2000), the most popular approach to obtain these parameters is Camera Calibration. Owing to the distinct pattern of chessboards, they are commonly used to calibrate cameras. Various photos of the chessboard were taken from different angles. As the exact dimensions of the chessboard were already known, the intrinsic parameters of the camera can hence be easily obtained using MATLAB Single Camera Calibration App. The obtained intrinsic parameters were exported for following applications.

After obtaining the intrinsic parameters through camera calibration, the next step is to measure the extrinsic parameters. While the camera's height can be measured easily, its pitch and yaw angles are not fixed, and can vary with the movement of the vehicle, which are mainly caused by road gradient and vibration. Therefore, these two extrinsic parameters need to be measured automatically at each time step to maximize the accuracy of distance estimation.

As the camera's pitch and yaw angles have direct influence on the coordinates of the vanishing point, this relation can be used to compute both angles. Owing to perspective effect, parallel lines will converge at the vanishing point in each image. Thus, these lines need to be identified in the image to locate vanishing point coordinates. Lane markers are hence selected, as they are prominent features on structured roads.

While there have been some applications that use either Hough transform or curve fitting to identify lane markers, it was found that these methods tend to be computational expensive, especially for long and high resolution videos. Thus, a novel and effective lane-marker detection approach was created.

Each video frame is first converted to grayscale, and vertically divided into 48 sections to reduce computation complexity. As lane markers are white, they will have larger intensity than adjacent road surface, and hence larger values in grayscale. Therefore, there will be pulses in grayscale values, which can indicate the horizontal locations of both edges of lane markers. Thus, this pulse feature in grayscale can be used to locate lane markers. Meanwhile, in order to exclude some false positives, which can be pulses caused by shadows or other interference, a grayscale threshold and a width threshold need to be assigned. This is because owing to the distinct feature of lane markers and road surface, the pulse representing lane markers will have a relatively large amplitude and short wavelength. As light conditions have a vast influence on grayscale values, the grayscale threshold is hence needed to be adaptive to improve its robustness. Thus, Otsu's method is used to compute this threshold by minimizing the intra-class variance of black and white pixels (Sezgin and Sankur, 2004). Moreover, in order to distinguish lane markers from other white objects, the width feature is adopted for isolation. This is because lane markers are much thinner than other white objects. Thus, in each row of grayscale data, the pulses denoting white objects are located, and their wavelengths are measured. Afterwards, a predefined width interval is used to distinguish lane markers.

With pixels denoting lane markers detected, they are hence classified into corresponding groups. Each group contains all pixels for a same lane marker. Afterwards, polynomial fitting is used to generate the desired parallel lines. The intersections of these lines are also calculated, and the clustering approach proposed by Rodriguez and Laio (2014) is performed to classify all intersections. The members within each cluster are accumulated, and the centre of the largest cluster is regarded as the vanishing point.

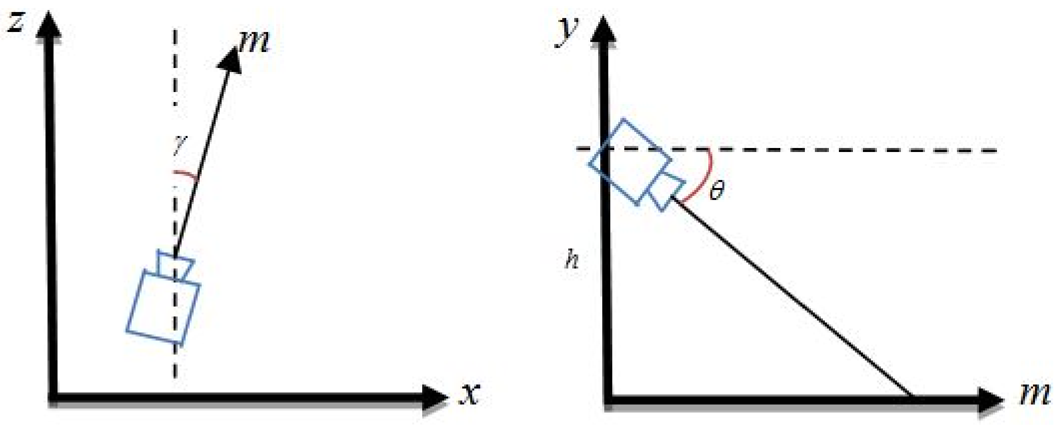


Figure 4.11. Camera pitch and yaw angle

After the vanishing point is located, the transformation matrix between image frame and world frame can hence be calculated accordingly. Prior to forming the matrix, the remaining two extrinsic parameters need to be computed using the vanishing point. As illustrated in figure 4.11, the equations for pitch and yaw angles can hence be derived as (Nieto et al., 2007),

$$\theta = arctan\left[tan\partial_v\left(1-\frac{2y}{N}\right)\right] \quad \textbf{4.1}$$

$$\gamma = arctan\left[tan\,\partial_h\left(\frac{2x}{M}-1\right)\right] \quad \textbf{4.2}$$

Where:

θ	Pitch angle
γ	Yaw angle
∂_v	Camera vertical aperture
∂_h	Camera horizontal aperture
x,y	Vanishing point coordinates
M	Image length in pixels

N	Image width in pixels

With all camera parameters computed, the transformation matrix between pixel coordinates and world coordinates can hence be obtained following the relations illustrated in figure 4.10.

$$T_1 = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \\ A_{41} & A_{42} & A_{43} \end{bmatrix} \quad \mathbf{4.3}$$

$A_{11} = -h \times \frac{c2}{f_x}; A_{21} = h \times \frac{s2}{f_x}, A_{31} = A_{41} = 0;$

$A_{12} = h \times s1 \times \frac{s2}{f_y}; A_{22} = h \times s1 \times \frac{c2}{f_y};$

$A_{32} = h \times \frac{c1}{f_y}; A_{42} = -\frac{c1}{f_y};$

$A_{13} = h \times c2 \times \frac{p_x}{f_x} - h \times s1 \times s2 \times \frac{p_y}{f_y} - h \times c1 \times s2;$

$A_{23} = -h \times s2 \times \frac{p_x}{f_x} - h \times s1 \times c2 \times \frac{p_y}{f_y} - h \times c1 \times c2;$

$A_{33} = -h \times c1 \times \frac{p_y}{f_y} + h \times s1; A_{43} = c1 \times \frac{p_y}{f_y} - s1.$

Where:

h	Camera height
f_x,f_y	Camera focal lengths
p_x,p_y	Camera optical centre coordinates
s1	Sine value of pitch angle
c1	Cosine value of pitch angle
s2	Sine value of yaw angle
c2	Cosine value of yaw angle

With the transformation matrix formulated, the next procedure is to detect the vehicle in each image and obtain its pixel coordinates. As taillights of the leading vehicle are red and close to each other in a horizontal plane, this distinct feature can be used to detect the leading vehicle. Moreover, as shown in figure 4.12, a trapezoid region in front of the host vehicle is selected as the search area to eliminate noises caused by sign plates and reduce computation complexity.

After searching in the region of interest, potential red candidates are indexed and sorted. Each pair of red objects that satisfy the vertical and horizontal tolerance is grouped and the closest pair is regarded as taillights of the leading vehicle. The centroids of this pair are extracted and averaged to represent the pixel coordinates of the leading vehicle.

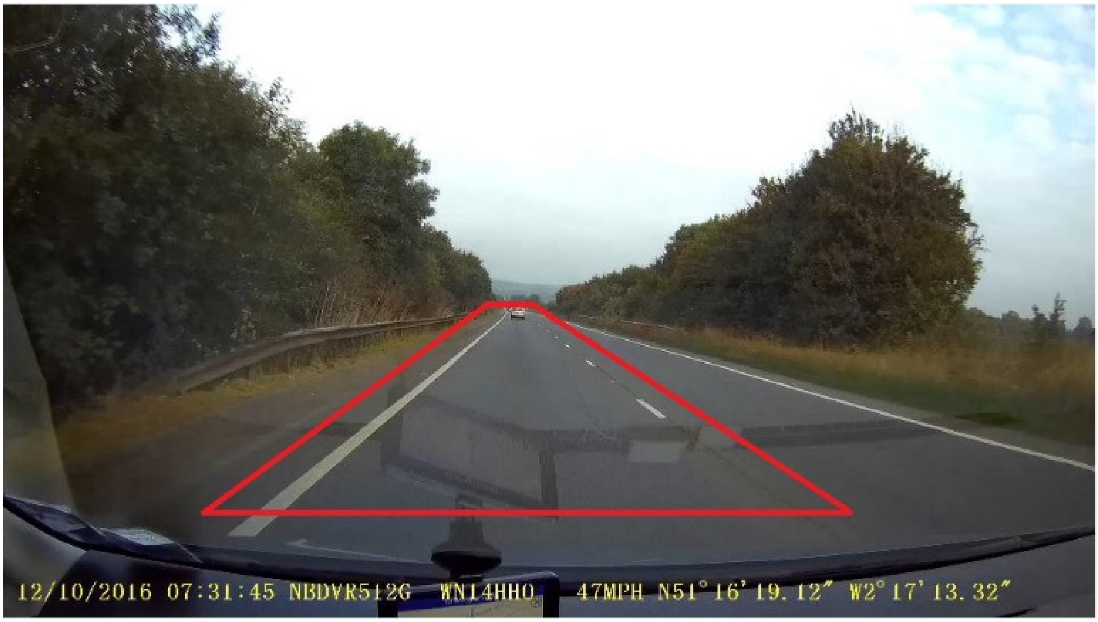


Figure 4.12. Leading vehicle detection zone

Assuming the transformation matrix is T_1 and vehicle pixel coordinates are (p_u,p_v), the distance between the leading vehicle and host vehicle can hence be easily obtained. Firstly, rearrange the vehicle coordinates as homogenous coordinates $(P_u, P_v, 1)^T$, and multiply it with the transformation matrix T_1, can result in,

$$\begin{bmatrix} W_x \\ W_y \\ W_z \\ W \end{bmatrix} = T_1 \times \begin{bmatrix} P_u \\ P_v \\ 1 \end{bmatrix} \qquad \textbf{4.4}$$

Therefore, the coordinates of the detected vehicle in the world frame are (W_x/W, W_y/W, W_z/W). According to the world frame shown in figure 4.10, the headway distance can hence be derived as W_y/W.

Meanwhile, as illustrated in figure 4.6, there is a fixed mounting deviation between the radar and camera. Therefore, a transformation matrix needed to be established first to convert both sensory measurements into a mutual coordinate frame. The corresponding coordinate frames and mounting deviations are illustrated in figure 4.13.

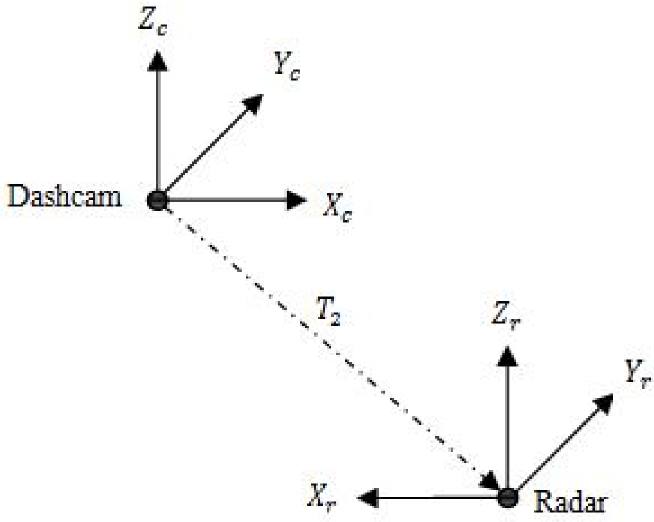


Figure 4.13. Coordinate frame conversion between radar and dashcam

Thus, the transformation matrix T_2 between the radar and camera can be derived as,

$$T_2 = \begin{bmatrix} -1 & 0 & 0 & 0.25 \\ 0 & -1 & 0 & -1.46 \\ 0 & 0 & 1 & 1.32 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \textbf{4.5}$$

As the radar can measure multiple objects in each cycle, post processing is hence implemented to extract useful data from the decoded files. In order to isolate data representing the leading vehicle from all radar measurements, camera footage is hence used for the detection and localization of the leading vehicle. Thus, the leading vehicle is first identified within each video frame. Afterwards, its pixel coordinates are used to multiply with the transformation matrix between the pixel and world frame T_1 to compute its world coordinates within the camera frame. The position of the leading vehicle within the radar frame can hence be obtained by multiplying the computed result with the transformation matrix between radar and camera frame T_2. Afterwards, a small search zone is created around this position to locate corresponding radar measurements. Meanwhile, as the original frame rate of the dashcam is 30 Hz, which is much slower than the radar updating frequency, the same search zone is used until the next video frame is updated. Moreover, as the leading vehicle position should be rather consistent between every two adjacent frames, its consistency is also checked to exclude abrupt changes caused by interference.

With both sensory sources of headway distance, Kalman filter is adopted to fuse the measurements from both sensors to compensate the drawbacks of each individual sensor and obtain an optimised result. A typical Kalman filter contains two phases, predict and update. At each time step, a priori state and covariance estimates are first predicated using previous values and the system model. Afterwards, these priori estimates are updated according to sensory measurements. An optimised posteriori estimate of the state vector can hence be obtained through this process. The predict phase is defined as,

$$x_{k|k-1} = F_k x_{k-1|k-1} + B_k u_k \quad \textbf{4.6}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \quad \textbf{4.7}$$

Meanwhile, equations for update phase are,

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k\right)^{-1} \quad \textbf{4.8}$$

$$x_{k|k} = x_{k|k-1} + K_k\left(z_k - H_k x_{k|k-1}\right) \quad \textbf{4.9}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad \textbf{4.10}$$

Where:

x_k	True state at time k
F_k	State transition model
B_k	Control-input model
u_k	Control vector
P_k	Error covariance matrix
Q_k	Covariance of the process noise
K_k	Gain
H_k	Observation model

R_k	Covariance of the observation noise
z_k	Observation of the true state
I	Identity matrix

Meanwhile, as the camera can only measure headway distance, and radar measurement contains both distance and relative speed, the state vector of the proposed filter is hence defined as x_k = $[dis_k, vel_k]^T$, and the observation vectors of the camera and radar are defined as z_k = $[dis_{camera_k}]$, and z_k = $[dis_{radar_k}, vel_{radar_k}]^T$ respectively, The state vector and the corresponding error covariance matrix of the filter is updated when receiving new sensory measurements.

4.4 Driving style classification

After the real driving data of participated human drivers were collected and processed, the driving style of these participants should also be classified to facilitate the overarching aim of this research, which is to investigate the influence of different driving styles on fuel consumption through personalised driver modelling. Differentiating the driving style groups of these human participants can contribute to labelling the driving styles represented by each corresponding personalised driver models. Therefore, the next step of this research is proposed to develop a classification approach to differentiate the driving style variations of these participants.

Owing to the overwhelming energy crisis and the advent of vehicular sensing technologies, a recent emerging research trend was witnessed as using recorded vehicle information to analyse driving styles and their correlations with fuel consumption. Many pattern recognition methods have been adopted for classification. For example, Aljaafreh et al. (2012) and Al-Din et al. (2013) developed fuzzy logic based classifiers. Meanwhile, Macadam et al. (1998) and Meseguer et al. (2013) used Neural Network to differentiate driving styles. Moreover, other methods, such as K-means and hierarchical clustering (Constantinescu et al., 2010), K-nearest neighbors (Vaitkus et al., 2014), and self-organizing map (Albers and Albrecht, 2005) have also been applied for driving style classification.

Although these studies have successfully classified drivers into three or four labelled groups (aggressive, normal, defensive, etc.), they tended to assume each participant's driving style remained consistent within each trip, and neglect the potential driving style variations. While this assumption may be suitable for these studies, a more plausible approach is to divide each entire trip into several segments, as even an extreme aggressive driver may not maintain driving aggressively during the entire trip. Therefore, with an overarching aim of developing a personalised and humanized driver model, an event based classification approach was proposed, which focuses on differentiating the variations in each individual's driving pattern, and providing more objective driving style classification.

Meanwhile, most of existing studies only use vehicle state information for classification, as shown in table 4.3. While these vehicle-related parameters can certainly reveal different driving styles, it should be noted that the interaction with traffic flow could also be a major cause to the variations. For example, in the car-following scenarios, the headway distance to the leading vehicle can be a critical reveal of different driving styles, and the underlying trigger of the change in vehicle state. Therefore, some influential factors on driving styles can be lost if excluding traffic information, as drivers of different driving styles have diverse traffic anticipation preferences (Sagberg et al., 2015). Thus, driver's interactions with traffic flow should be included to improve the performance of driving style classification. Therefore, based on the collected real driving dataset, headway distance was hence selected to represent this interaction.

With the collected on-road driving data, SVC was selected for driving style classification. Inspired by SVM, SVC is an unsupervised clustering algorithm initially proposed by Ben-Hur et al. (2001). Owing to its performance in detecting arbitrary shape clusters with a hierarchical structure in high dimensional data (Yang et al., 2002), SVC has previously been used for pattern recognition (Ben-Hur et al., 2001) and image segmentation (Wang and Liu, 2015). As SVC is a relatively new classification algorithm, it hence has not been adopted for driving style research before. However, its supervised version (SVM) has already been used in some related research. For instance, Wang and Xi (2016) used vehicle speed and throttle opening as feature parameters, and developed an algorithm that combined K-means clustering and SVM to classify drivers into aggressive and moderate. Meanwhile, both driving performance and physiological measurements were used in a SVM-based classifier to distinguish drunk and normal driving (Chen and Chen, 2017). As the performance of this set of support vector based algorithms has been validated in many studies (Ben-Hur, et al., 2001; Yang et al., 2002; Wang and Liu, 2015; Wang and Xi, 2016; Chen and Chen, 2017), SVC was hence adopted as the classification algorithm in this research.

Table 4.3. Feature parameters for driving style classification

Authors	Year	Feature parameters
Aljaafreh et al.	2012	Longitudinal acceleration
		Lateral acceleration
		Vehicle speed
Al-Din et al.	2013	Longitudinal acceleration
		Vehicle speed
		Following distance
Dörr et al.	2014	Acceleration/deceleration
		Vehicle speed
		Time gap
		ACC activation
Macadam et al.	1998	Range
		Range rate
Meseguer et al.	2013	Acceleration
		Vehicle speed
		Engine speed
Constantinescu et al.	2010	Acceleration
		Vehicle speed
		Mechanical work

Vaitkus et al.	2014	Acceleration
Albers and Albrecht	2005	Acceleration
		Engine speed
		Transmission and wheels
		Path of gap and clutch pedals

4.4.1 Event detection

In order to segment each trip into separate event groups, a dynamic sliding window approach was developed. Four classes of driving events were derived as accelerating, braking, maintaining, and stop. Each class of events was defined by fixed conditions, which can occur multiple times during every trip. The transitions between different events are illustrated in figure 4.14.

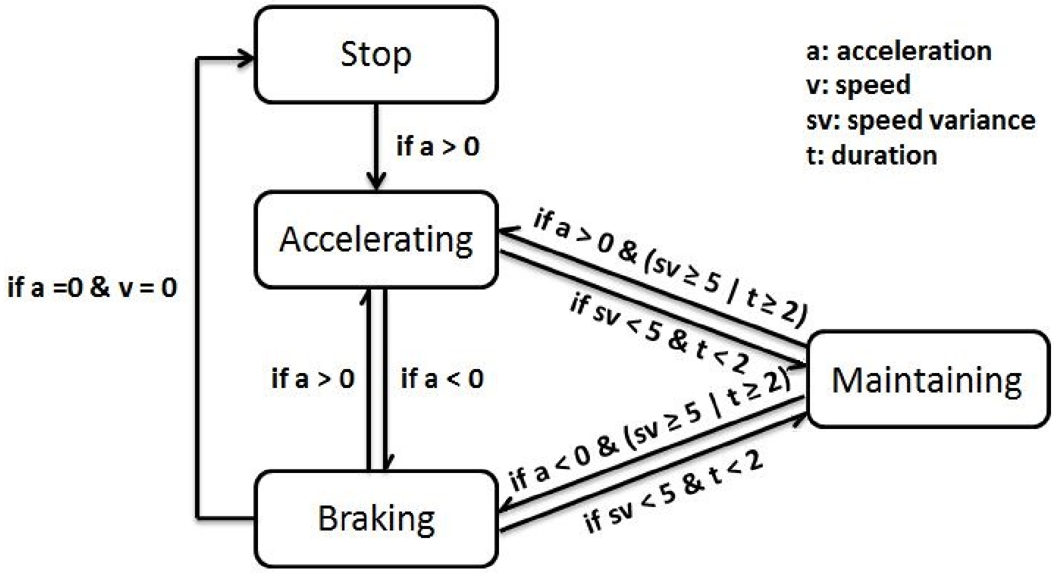


Figure 4.14. Transitions between events

As shown in figure 4.14, short accelerating or braking events with small speed changes are regarded as maintaining. Therefore, each trip data can be segmented into these four event groups using the above transition conditions. One segmented trip is illustrated in figure 4.15 to demonstrate this proposed method. It can be noted that there are 170 accelerating events, 131 braking events, 258 maintaining events and 19 stop events detected during this trip.

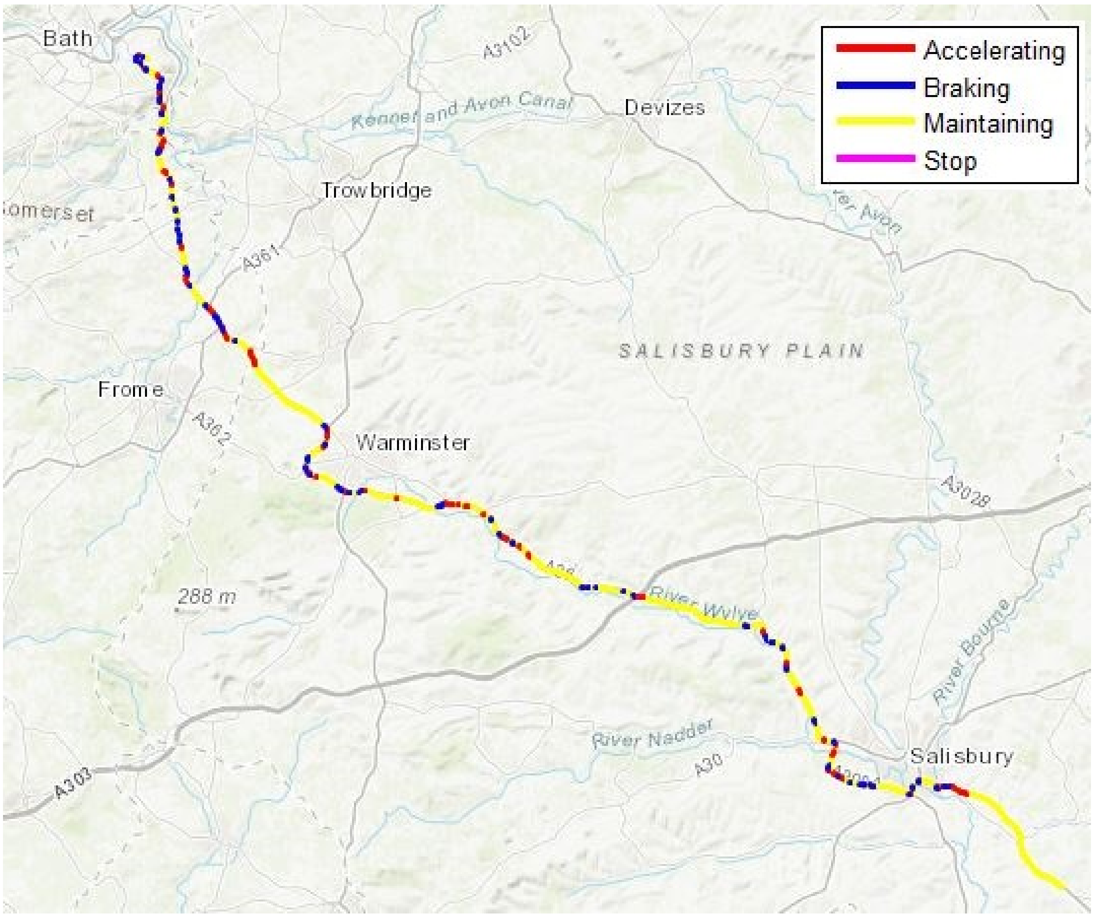


Figure 4.15. Event segmentation result of one selected trip

4.4.2 Feature parameter selection

With all driving data segmented into separate groups, the statistical features of each signal were first extracted. Four typical statistical features were identified as mean, standard deviation, maximum and minimum values. With four input signals, a 16-dimension statistical feature parameter was hence computed for each detected event.

Along with statistical features, spectral features of each signal were also captured, as ignoring the temporal dependencies can lead to skewed results (Hallac et al., 2016). This is because the measurement at one state is highly correlated with measurements at adjacent states. While most existing driving style studies only use statistical features for classification, spectral features have been adopted in two previous studies. One was implemented by Žylius et al. (2014). They used short-time Fourier transform to analyse accelerometer signals and classify driving styles as aggressive and safe. Meanwhile, DWT was implemented by Hallac et al. (2016) to achieve driver identification using driving data from a single turn. While both methods can be used to extract spectral features, DWT was selected in this study owing to its flexible time-frequency window.

While there are several different types of wavelet, Haar wavelet was selected for the transformation, as it is one of the most frequently used wavelets for non-smooth functions (Mallat, 2008). Originally proposed by Haar (1910), its mother wavelet function is defined as,

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 0.5 \\ -1 & 0.5 \leq t < 1 \\ 0 & otherwise \end{cases} \qquad \textbf{4.11}$$

The core of DWT is to compute approximation and detail coefficients by passing the original signal through a series of filters. As the feature of the original signal is preserved in these coefficients, they can hence be treated as the spectral feature parameters (Hallac et al., 2016).

Moreover, in order to ensure the computed spectral feature parameters have the same dimensions, measurements of events within a same group were resampled to a unified length. This length was dynamically defined by the longest event within the group. Using this resampling process, the dimensions of DWT vectors within each event groups were hence aligned.

After both statistical and spectral features were extracted, they were combined as feature parameters for classification. However, it should be noted that the dimensions of these parameters were quite large, and hence unsuitable for further processing. In order to reduce the dimensions of feature parameters and improve the clustering speed, PCA was hence implemented. PCA is a statistical method that uses orthogonal transformation to convert correlated variables into linearly uncorrelated variables. The converted variables are referred to as principal components, with each principle component accounts for as much of the variability in the original data as possible. Therefore, deciding the number of principle components is crucial to dimension reduction.

While there are four commonly used criteria for this selection, which are, a) visual interpretation of the scree plot for the “elbow”, b) eigenvalues larger than 1.0, c) meaningful percentage of variance, and d) interpretable components, the third criterion was selected in this study, as it can efficiently reduce the dataset to 2-3 components (Constantinescu et al., 2010). Therefore, selected principal components were required to represent at least 95% variance of original data.

4.4.3 SVC

After the PCA process, SVC was hence performed on those selected principal components to classify each event into different driving style groups. According to Ben-Hur et al. (2001), SVC has two main steps, which are SVM Training and Clustering Labelling. The first step aims to construct cluster boundaries. The original data is mapped into a high dimensional feature space using a Gaussian kernel function, which can be represented as,

$$K(x_i, x_j) = e^{-q||x_i - x_j||^2} \quad \textbf{4.12}$$

Where:

q	Width parameter

Afterwards, the smallest sphere that encloses the image of feature points is searched, which can be described as,

$$||\phi(x_j) - a||^2 \leq R^2 + \xi_j \quad \textbf{4.13}$$

Where:

a	Sphere centre
R	Radius
ξ_j	Slack variable

Lagrangian with penalty term is hence introduced to solve this problem,

$$L = R^2 - \sum_j \left(R^2 + \xi_j - ||\phi(x_j) - a||^2\right)\beta_j \quad - \sum_j \xi_j \mu_j + C \sum_j \xi_j \quad \textbf{4.14}$$

Where:

β_j,μ_j	Lagrange multipliers

$C\sum_j \xi_j$	Penalty term

Therefore, the distance of point x to sphere centre in feature space can be derived as,

$$R^2(x) = K(x,x) - 2\sum_j \beta_j K(x_j, x) + \sum_{i,j} \beta_i \beta_j K(x_i, x_j) \qquad \textbf{4.15}$$

The cluster boundaries can hence be determined by contours that enclose the points in data space given by,

$$\{x|\, R(x) = R\} \qquad \textbf{4.16}$$

During the second step, cluster labels are assigned to each data point. As this cluster labelling process can be time consuming, several different approaches have been proposed to improve the efficiency and accuracy of this procedure, such as CG, DD, MST, K-NN, and R-CG (Lee and Lee, 2006).

While these approaches were proposed in different studies, their performances have already been compared on the same data set (Lee and Lee, 2006). As the dimensions of feature parameters in this research were reduced to 2-3 using PCA, DD was hence selected as the cluster-labelling algorithm considering the trade-offs between labelling accuracy and time complexity.

4.5 Driver modelling and calibration

With the classified real driving data, the next step is to select an appropriate method to develop the driver model. As outlined in the previous chapter, owing to the incorporation of vagueness in measurements, fuzzy logic based driver model has a better similarity to human reasoning, Moreover, fuzzy logic models also have a high interpretability, and are more robust to incomplete data and less accurate traffic estimation. However, it should be noted that the determination of fuzzy rules and membership functions is a major challenge in developing fuzzy logic controllers. Therefore, the fuzzy logic driver model should be properly defined and calibrated to achieve better performance.

4.5.1 Baseline driver modelling

With the general procedure of fuzzy logic outlined in the previous chapter, it can be noted that fuzzy rules are the kernel of fuzzy logic and have a vast influence on its performance. Therefore, these rules need to be properly defined to improve controller performance. To define such rules, the input and output of the model need to be properly selected in advance. From drivers' perception perspective, multiple inputs can be received during driving, such as headway distance, relative speed to the leading vehicle, current vehicle speed, engine rpm, gear selection, pedal position, road gradient, time and weather. While all the information can have some influence on drivers' decision, it is unrealistic to consider all of them together, as the number of fuzzy rules will increase dramatically with multiple inputs. Thus, only the most prominent parameters, such as headway distance, current vehicle speed, gear selection, and pedal position, were selected to simplify the rule composition. Meanwhile, two sets of headway distance were derived to improve the similarity to human driver. While the actual distance measurement was used in short range, the time gap measurement was adopted in middle and long ranges. This is particularly because the widely adoption of two-second time gap rule in most countries. It is commonly adopted by drivers to assess safety headway distance by counting two seconds using stationary references. While this rule is more likely a reaction time based guidance, it is particularly useful when the vehicle is traveling above certain speed, as physical distance to a distant leading vehicle can be difficult to estimate. However, this rule does not apply to slow moving vehicles, and physical distance can be easily estimated instead. Therefore, both time and distance based headway distance were used segmentally as model inputs, together with current vehicle speed, gear selection and pedal position. Meanwhile, the typical driver output can be denoted as throttle pedal movement, brake pedal movement, and gear shifting. As throttle and brake pedals cannot be activated simultaneously, and multiple output can increase the complexity of fuzzy rules, power demand was selected as the sole output to simplify the fuzzy logic controller. This generated output parameter contains information about the driver's intention. Thus, pedal movements and gear shifting can be derived from it accordingly. Therefore, the established baseline driver model can be denoted as figure 4.16.

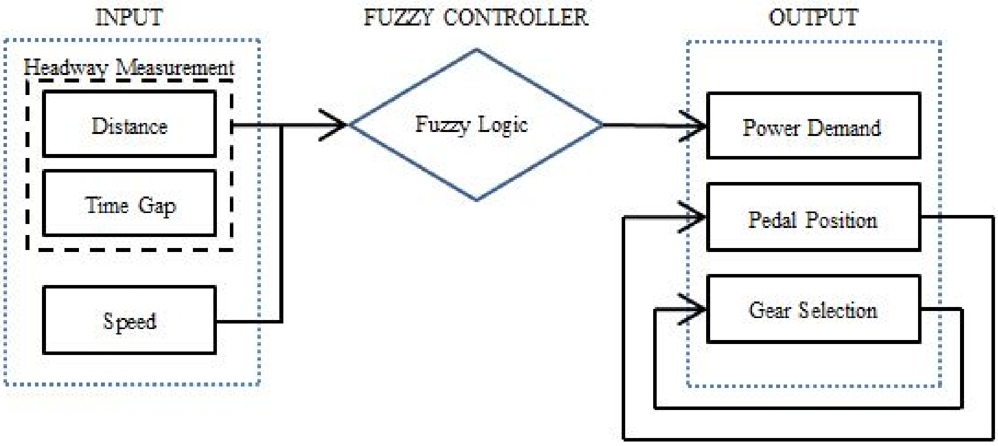


Figure 4.16. Architecture of the established driver model

After establishing the baseline driver model, the next step is to develop the demanded fuzzy controller through calibration with the real driving data. As there is currently no standard procedure of the determination of fuzzy rules and membership functions, two recommended calibration approaches were separately adopted to develop the desired fuzzy controller.

4.5.2 Fuzzy controller calibration approach I

The first calibration approach is mainly based on the theory and method proposed by Yadav and Yadav (2015). According to experts' knowledge, five linguistic terms were derived for time gap (Very Small, Small, Middle, Large, Very Large), current vehicle speed (Very Slow, Slow, Appropriate, Fast, Very Fast) and power demand (Harsh Decelerate, Slight Decelerate, Maintain, Slight Accelerate, Harsh Accelerate) respectively, and three for distance measurement (Close, Medium, Far).

Meanwhile, based on the number of variables, 15 rules were derived for the distance based model, and 25 rules for the time gap model. The created rules share a similar structure, and one example can be described as,

IF *headway_distance* is *Close* AND *vehicle_speed* is *Fast* THEN *power_demand* is *Harsh Decelerate*.

The control surfaces of both rule sets are illustrated in figure 4.17.

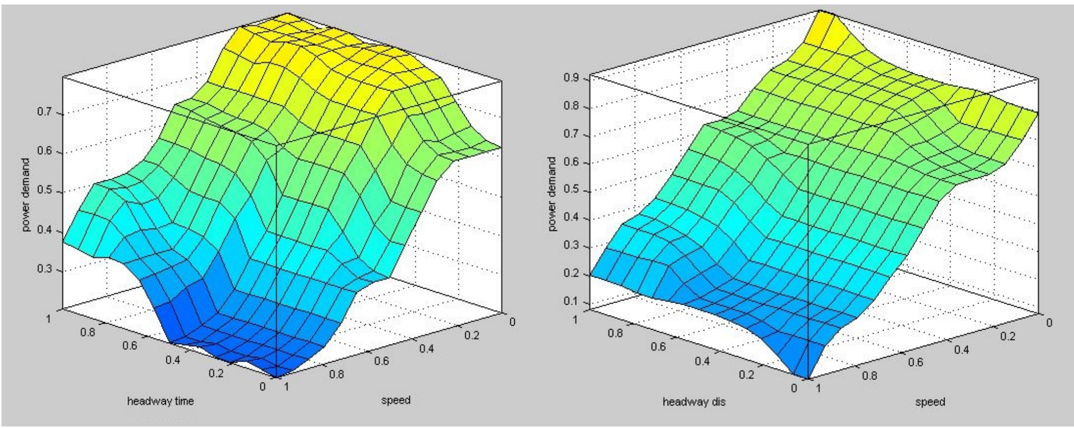


Figure 4.17. Control surfaces (time: left; distance: right)

Moreover, the inference engine was selected to be Mamdani, as it is the most commonly used inference system. Meanwhile, the defuzzification approach was selected to be the centre of mass.

Meanwhile, Triangular-shaped membership functions were selected for each variable, which can be denoted as

$$f(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \qquad \textbf{4.17}$$

Where:

a, b, c	Determine thresholds of the membership function

As these thresholds have a vital influence on the performance of the established fuzzy controller, they need to be properly determined to optimise the controller. Therefore, these parameters should be calibrated using the collected real driving data. For variable containing five linguistic terms, there were 15 parameters associated with its membership function, and 9 for variable with three linguistic terms. Car-following scenarios were isolated from the collected three months real driving data to calibrate these parameters. The recorded headway distance data and vehicle state information were synthesized and paired with the driver's intention, which was denoted by pedal movements and gear selection.

According to the theory proposed by Yadav and Yadav (2015), each category of data was first sorted in ascending order, and then K-means clustering was performed to cluster these values into separate groups. The number of clusters was determined by the quantity of linguistic terms for each variable. Meanwhile, the cluster center value was assigned to b, the central vertex parameter. Moreover, the similarity value between adjacent data were computed as,

$$S = \begin{cases} 1 - \frac{v_{i+1} - v_i}{C \times \sigma_s}, & if\ v_{i+1} - v_i \le C \times \sigma_s \\ 0, & else \end{cases} \quad \textbf{4.18}$$

Where:

S	Similarity
v_i	*i*th data
C	Control parameter
σ_s	Standard derivation of $v_{i+1} - v_i$

Afterwards, the minimum value of similarity in each cluster was selected as the membership value of two boundary points for that cluster. Therefore, the remaining two defining parameters can hence be computed as,

$$a = b - \frac{b - y_{min}}{1 - S_{min}} \quad \textbf{4.19}$$

$$c = b + \frac{y_{max} - b}{1 - S_{min}} \quad \textbf{4.20}$$

4.5.3 Fuzzy controller calibration approach II

The second calibration approach is the ANFIS with hybrid learning algorithm proposed by Jang (1993). This training algorithm is a combination of the least-squares and back-propagation gradient descent methods, which can achieve a faster convergence rate and better performance in avoiding local minima. The architecture of this ANFIS is shown in figure 4.18.

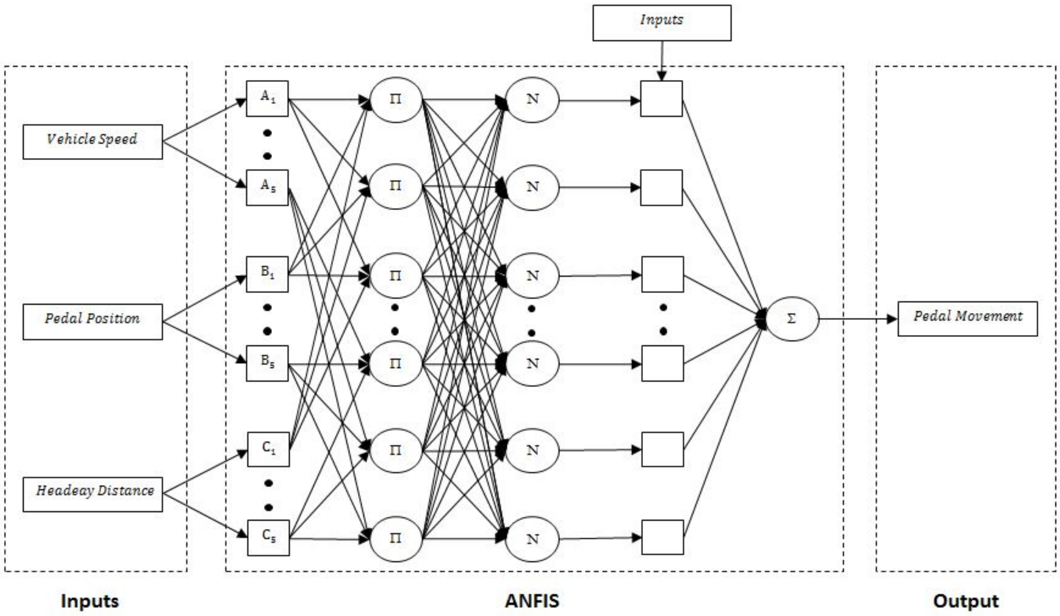


Figure 4.18. Architecture of the established ANFIS

It can be noted from figure 4.18 that the established ANFIS has five layers. A brief description of each layer is discussed below:

Layer 1: This is the fuzzification layer, with each node representing a specific linguistic variable of input parameters. There are a total of 15 nodes in this layer. 5 nodes (Very Slow, Slow, Medium, Fast, Very Fast) for vehicle speed, 5 nodes (Very Small, Small, Medium, Large, Very Large) for pedal position, and 5 nodes (Very Close, Close, Medium, Far, Very Far) for headway distance. The Gaussian member-ship function is selected. The output of each neuron is the degree of membership, which can be represented as,

$$O_{1i} = \mu_{A_i}(x) = exp\left[-\frac{(x-c_i)^2}{2a_i^2}\right] \qquad \textbf{4.21}$$

Where:

a_i, c_i	Premise parameters

Layer 2: This layer contains the fuzzy rules. Each neuron corresponds to a Sugeno type fuzzy rule. The output of each node is the product of all inputs:

$$O_{2i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y)\mu_{C_i}(z) \qquad \textbf{4.22}$$

Where:

w_i	Firing strength of each rule

Layer 3: The normalized firing strength is calculated in this normalization layer, which can be denoted as.

$$O_{3i} = \overline{w}_i = \frac{w_i}{\sum_i^n w_i} \quad \textbf{4.23}$$

Layer 4: This is the defuzzification layer, where the weighted consequent value of a given rule is determined as,

$$O_{4i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i z + s_i) \quad \textbf{4.24}$$

Where:

p_i, q_i, r_i, s_i	Consequent parameters

Layer 5: There is a single neuron in this output layer. Its generated value is determined as the summation of all outputs from previous layer, which can be denoted as,

$$O_{5i} = \sum \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \textbf{4.25}$$

In order to evaluate the tuning performance of ANFIS, the collected real driving data were randomly divided into two subsets. 70% of the data were used as training data to calibrate the model, and the remaining 30% were used as testing data for evaluation.

4.5.4 Gear shifting strategy

Along with the modelling of the driver's pedal control behaviour, gear-shifting strategy should also be personalised to improve the performance of the established driver model. While several factors (vehicle speed, engine speed, gradient, overtaking, etc.) can affect driver's decision on gear selection, only the first two factors were considered owing to the lack of relevant data of road gradient and the attempt of overtaking. Moreover, as the developed driver model will be adopted to direct control a robot driver in future studies, these two factors also correspond with the settings of the robot. This is because for safety concern in the direct control mode, the robot driver only offers two modes of gear shifting strategies, based either on vehicle speed or engine speed.

In order to determine the gear shifting strategy of the driver model, the collected vehicle state data were used to infer underlying relations. However, it should be noted that the gear selection information was not directly recorded by the data logger. Therefore, an estimation approach was developed based on direct relations among gear selection, vehicle speed, and engine speed. While the gear selection cannot be directly computed using the transmission formula, as the values of some influential parameters (the final drive ratio and tire diameter) were not acquired, the testing data of the same vehicle driven by the robot driver on chassis dynamometer were available. As these testing data contain the gear selected by the robot, the mapping relation between vehicle speed, engine speed and selected gear, was hence formulated. This relation was then used to infer the selected gear of the instrumented vehicle during on-road driving.

After the gear selection data were acquired, the next procedure was to determine the most influential factor on the gear shifting. Therefore, a correlation analysis was conducted between gear selection, vehicle speed and engine speed. Pearson's linear correlation coefficients were computed to evaluate the underlying relations, which can be described as,

$$rho(a,b) = \frac{\sum_{i=1}^{n}(X_{a,i}-\overline{X_a})(Y_{b,i}-\overline{Y_b})}{\sqrt{\sum_{i=1}^{n}(X_{a,i}-\overline{X}_a)^2\sum_{j=1}^{n}(Y_{b,j}-\overline{Y}_b)^2}} \qquad \textbf{4.26}$$

Where:

n	Sample size
$X_{a,i}$, $Y_{b,i}$	Individual sample points
$\overline{X_a}$, $\overline{Y_b}$	Sample mean

Along with the evaluation of the most influential factor on gear shifting through correlation analysis, the transit thresholds between different gears should also be determined from the collected real driving data. It should be noted that for a given gear selection, vehicle speed can vary within range. Therefore, there can be two possible gear selections for a certain range of vehicle speed, which is the intersection of corresponding vehicle speed ranges of two adjacent gear selections. In order to determine the transit threshold, the probability distributions of two adjacent gear selections within the intersection range are computed. The intersection point of the fitted probability distribution curve is treated as the transit threshold. Therefore, the lower gear is selected in the vehicle speed range smaller than the threshold, while the higher gear will be chosen when vehicle speed is larger than the threshold.

4.6 Simulation environment

4.6.1 Vehicle model

To facilitate the evaluation of the established driver model, a vehicle model that possesses the essential features of the instrumented vehicle was developed. Using the vehicle specification listed in table 4.1, a vehicle model was developed in Simulink, a graphical programming environment for modelling, simulating and analysing multi-domain dynamical systems.

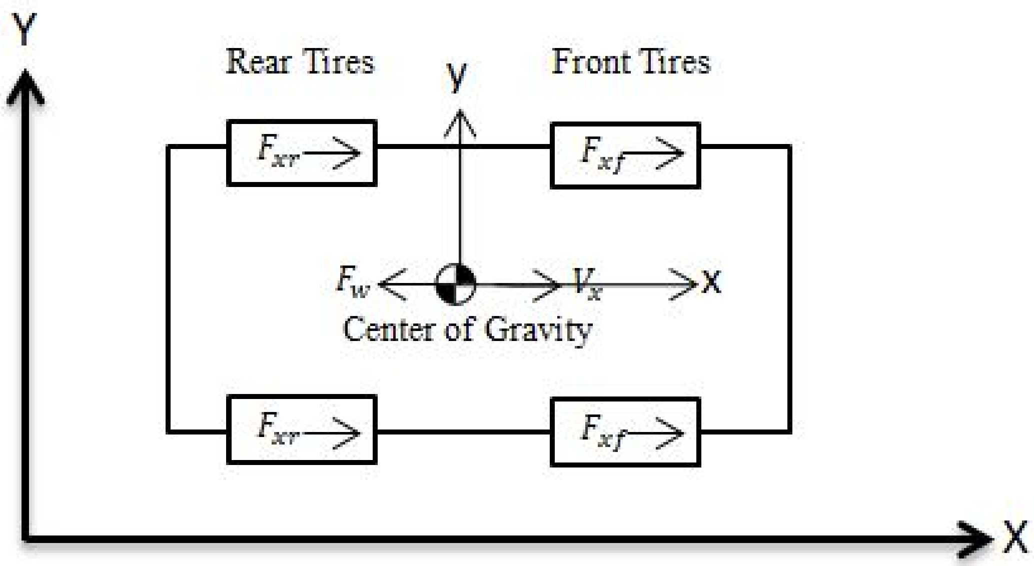


Figure 4.19. Vehicle dynamic relation

The established vehicle model consists of five subsystems, which are engine, vehicle body, tires, brake, and transmission. For the engine subsystem, a Generic Engine model was directly selected from Simulink's predefined drivetrain library, SimDriveline. This model was then parameterized to represent the diesel engine of Sharan. Meanwhile, for the vehicle body subsystem, the adopted dynamic relation of the vehicle is illustrated in figure 4.19.

Thus, it can be noted that the vehicle dynamics can be defined as

$$\dot{V_x} = \frac{2F_{xr}+2F_{xf}-F_w}{M} \quad \textbf{4.27}$$

Where:

M	Vehicle mass
F_{xf}	Tractive forces on front tires
F_{xr}	Tractive forces on rear tires
F_w	Wind drag force

Moreover, a set of magic formula based tire models were used to simulate the interactions between tire and road. As proposed by Pacejka and Bakker (1991), the magic formula can be used to calculate the forces acting from road to tire, which can be denoted as

$$F_x = D\sin\{C \cdot arctan[B(1-E)k + E \cdot arctan(Bk)]\} \quad \textbf{4.28}$$

Where:

D	Peak factor
C	Shape factor
B	Stiffness factor
E	Curvature factor
k	Slip parameter

The established brake subsystem was connected to tire models through a shaft. This subsystem can directly convert brake signals to corresponding actuator forces and hence generate friction torques on the connection shaft. Moreover, a six speed manual gearbox was also developed to represent the transmission subsystem. The clutches were used to engage and disengage different gear sets. The gear ratios were assigned according to the specifications in table 4.1. Meanwhile, a vehicle speed based gear shifting strategy was also created.

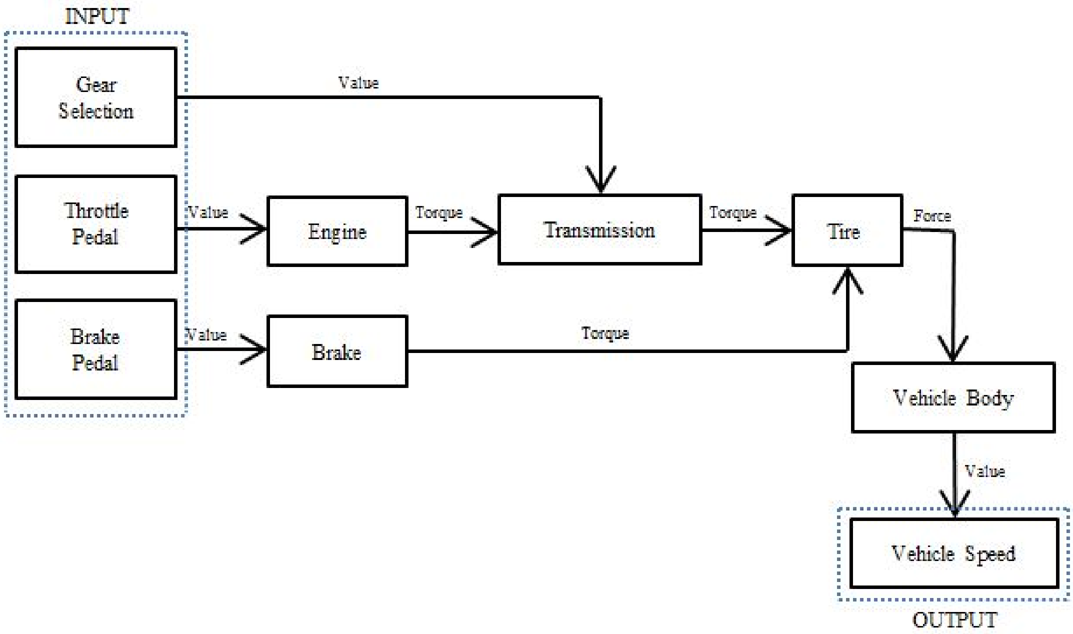


Figure 4.20. Architecture of the established vehicle model

The vehicle model was solely built in Simulink. It consists of five subsystems, and some existing SimDriveline blocks, such as generic engine, gear and clutch, were also incorporated in the model. The overall architecture of the established vehicle model was illustrated in figure 4.20.

4.6.2 Simulation scenario

To model different driving style, a simulation scenario needs to be developed for examination. As the ultimate aim of developing this driver model is to introduce driving styles into drive cycle and RDE experiments, the simulation scenario was hence based on the latest drive cycle, WLTC.

As the established driver model was calibrated using real diving data collected from a VW Sharan, which power-weight ratio is larger than 34, the Class 3 WLTC test cycle was hence selected (Tutuianu et al., 2014). The speed profile of this test cycle is illustrated in figure 4.21.

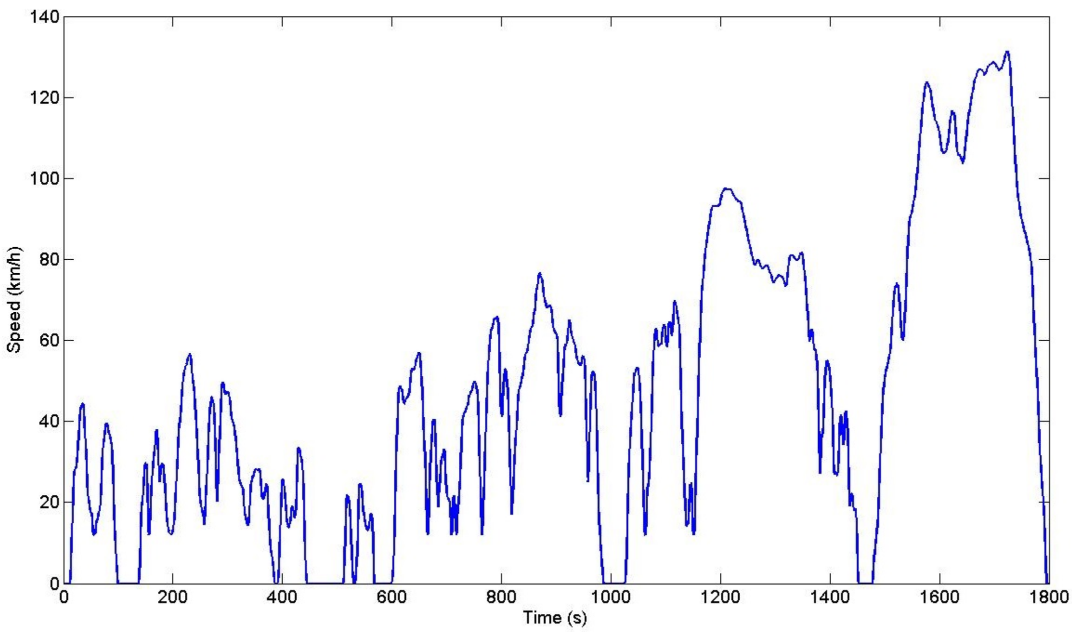


Figure 4.21. WLTC Class 3 speed profile

In order to introduce driving style into this drive cycle data, one possible solution is assuming the driver is instructed to follow this speed profile. Therefore, the driving style variations can be partially reflected in the oscillations, convergent speed and tracking accuracy. While these parameters can reveal the influence of driving style to a certain extent, they are not directly correlated, especially from the driver's perception. Another simulation scenario was hence proposed to increase the similarity to the real driving environment. While driving style variations can be reflected in many different scenarios, such as car-following, free flow, and following driving instructions, car-following scenarios are of particular interest. This is because car-following behaviour consists of two aspects: the preferred acceptable headway distance, and the driving pattern (accelerating, braking, etc.) according to the movements of the leading vehicle (Sato and Akamatsu, 2012). It can be noted that most driving styles can be well reflected in both aspects. Moreover, the headway distance feature has a high correlation with driver's motivation to change vehicle state, and is hence an important factor in driver's perception. Therefore, creating a car-following simulation scenario can help to reveal driving style variations, and hence incorporate them into drive cycle tests.

In order to create such a simulation scenario, an imaginary leading vehicle is introduced, which performs the WLTC speed profile. Thus, instead of directly providing the drive cycle data to the driver model, the drive cycle information is converted as the headway distance variations between the model and the imaginary leading vehicle. This setting can hence allow the driving style variations recorded in real world car-following scenarios to be reflected in procedures that are anchored to the standard drive cycle tests. While this setting can increase the difference between actual and target speed profiles, the similarity to human drivers is improved and the influence of driving style is more directly revealed.

4.7 Chapter summary and conclusions

This chapter provides a general description of all the adopted methods in this study. Divided into five subsections, the theory foundations of real world data collection, driving data processing, driving style classification, driver modelling and calibration, and simulation environment, are separately presented.

In order to collect sufficient real world driving data, a VW Sharan was instrumented with a data logger, a dashcam, and a long range radar. A route starts from the university campus and ends near Salisbury was selected for data collection, which covers a distance of approximately 45 miles. Extensive driving data of one driver were collected for three continuous months, while two other human drivers also participated in the data collection process. The collected real driving data consist of three components, radar measurements, the dashcam video footage, and the ECU information recorded by the data logger. To ensure the safety of the collected data, two backups were stored, one was in an external hard driver, while the other was uploaded to the university’s server. The total file size was approximately 1.93 TB.

With the collected driving data, a pre-processing was implemented to extract useful information from the raw data. While the ECU information can be easily interpreted using provided software, a Python-based decoding software was developed for the raw radar measurements. Moreover, in order to compensate the drawbacks of using an individual sensor, the dashcam footage was also processed to provide another source of headway distance measurements. With the pre-determined camera's intrinsic and extrinsic parameters, the transformation matrix between the world coordinates and pixel coordinates was formulated based on IPM. Meanwhile, the vehicle's pixel coordinates were determined through the identification of tail lights. Therefore, the headway distance can be measured accordingly. Afterwards, both sensory data were fused using Kalman filter to generate an optimised headway distance measurement, which was later synchronised with ECU information to form the real driving dataset.

Afterwards, a driving style classification approach was developed to differentiate the driving style variations from the collected driving data. Each trip data were first segmented into four driving events (accelerating, braking, maintaining, and stop) using the proposed event detection algorithm, which is a dynamic sliding window approach based on hard boundaries. Afterwards, the spectral features of each parameter were computed using DWT, and combined with the corresponding statistical features to form the basis of parameter selection. Meanwhile, PCA was performed to reduce the dimension of feature parameters and extract the most prominent components, which were fed into SVC for driving style classification.

With the classified real driving data, two fuzzy logic calibration methods were adopted for driver modelling. The first approach is based on the theory proposed by Yadav and Yadav (2015), which performs K-means clustering to calibrate membership functions, and require some additional expert knowledge to define the rules. Meanwhile, the second approach is proposed by Jang (1993), and uses a neural network to infer the structure of the fuzzy logic controller.

Finally, a simulation environment was developed to facilitate the evaluation of the calibrated driver models. A Simulink-based vehicle model was first developed, which consists of five subsystems, namely engine, vehicle body, tires, brake, and transmission. This vehicle model was integrated with the driver model to help the evaluation of the established driver models and facilitate the investigation of the influence of driving style on fuel consumption. Meanwhile, a simulation scenario that is anchored to the standard WLTC drive cycle was also proposed. This setting allows better revealing the potential variations of driving style, and increasing the significance of this research.

With the theories of all the adopted methods presented in this chapter, the obtained corresponding results of this research will be shown in the following chapters.

Chapter 5 – *Real driving data collection*

This chapter mainly presents the results from the implementation of real driving data collection and processing. Following the methodology outlined in section 4.3, the measurement accuracy of radar is evaluated first. Afterwards, the processing algorithm of dashcam is examined. The correlation between both sensors is then checked, and the optimizing performance of Kalman filter is finally assessed. A short trip data is extracted in this chapter to demonstrate the performance of the proposed algorithm. The results are presented in five sections, discussing the performance of each individual sensor, the correlation between them, optimisation with Kalman filter, and chapter summary and conclusions respectively.

The results illustrated in this chapter have been presented at the SAE Intelligent and Connected Vehicles Symposium.

5.1 Radar

An experiment was implemented to assess the performance and accuracy of the radar. In this scenario, the host vehicle remained static and distances to all targets were manually measured for comparison. The performance of detecting multiple random objects was examined to justify the radar. The test scenario and detected objects were illustrated in figure 5.1.

Figure 5.1. Radar measurements and targets

Five objects were detected by the radar in this scenario. The obtained radar measurements were listed in table 5.1.

Table 5.1. Radar measurements

Object ID	1	2	3	4	5
Lateral offset (m)	0	2	-1	-4	-4
Longitudinal distance (m)	5	5	5	18	22
Measured distance (m)	4.95	4.95	5.38	17.88	22.32

It can be noted that the radar measurements tend to be rounded to integers. While the longitudinal distances between the radar and manual measurements were not exactly the same, the largest difference was 0.38m. This value was satisfying as human driver's estimation about the headway distance will be less accurate than this radar. Thus, the radar data can be regarded as absolute measurements and used to improve accuracy of Kalman filter.

While the radar measurements can be directly retrieved, the distance from dashcam requires more computations. Therefore, the validation of camera measurements is divided into four steps, road recognition, vanishing point detection, vehicle detection, and distance computation.

5.2 Visual sensing

5.2.1 Road Recognition

As the basis of distance estimation with a dashcam, the lane marker detection is crucial to the accuracy of the algorithm. Therefore, the performance of this proposed detection approach needs to be fully assessed. As light condition has a significant influence on the image's grayscale values, various scenarios should be examined to validate the proposed algorithm. Therefore, a straight segment of A36 between Standerwick and Woolverton was selected, and images along the route were taken at different time and dates to maximize the likelihoods of light conditions.

As shown in figure 5.2, six images of various time and weather conditions are recorded. Figure 5.2a, 5.2b and 5.2c illustrate normal weather in the morning, afternoon and evening, while 5.2d, 5.2e, 5.2f show foggy, sunny and rainy respectively. It can be noted that only two lane markers lighted by headlights were detected at evening, and all three lane-markers were detected in other figures. Meanwhile, although the differences between most figures are not prominent to visualize, the grayscale values vary among them. As listed in table 5.2, the largest variance is 30.92% between morning and evening. As these figures generally contain all possible weather conditions, it can be noted that the proposed algorithm can detect parallel lane markers accurately in most scenarios. Meanwhile, it is interesting to find that the average grayscale values of different weathers almost remain the same. It indicates that weather condition has a much less influence on average grayscale than presumed.

Therefore, this proposed lane marker detection based on Otsu's method is robust to different weather conditions.

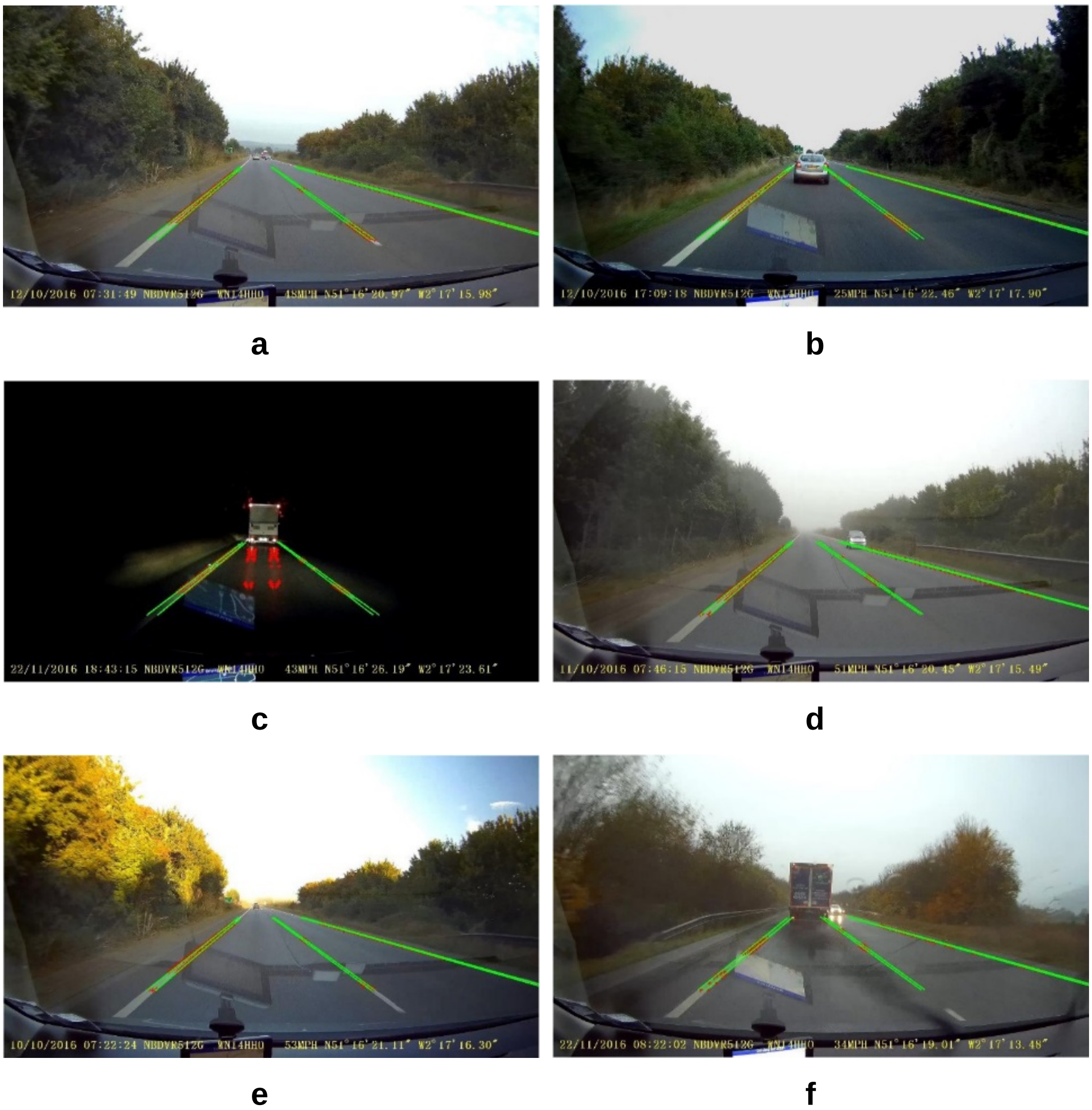


Figure 5.2. Lane marker recognition

Table 5.2. Average grayscale values

Figure	Morning	Afternoon	Evening	Fog	Sun	Rain
Average Grayscale	161	130	82	158	149	149

5.2.2 Vanishing point detection

After the performance of road recognition algorithm was validated, the next procedure was to locate the vanishing point based on detected parallel lines. As described in the previous section, k-means is used to classify the intersections of these lines, and the centre of the largest cluster is regarded as the vanishing point. In order to validate this hypothesis, the same straight road was used for examination. This is because the vanishing point position should be rather consistent along a straight road. The total covered distance was 600m, and travel time was 57s. Meanwhile, the frequency of frame processing was set to 2 Hz, leading to a sum of 114 frames. Therefore, a total of 114 vanishing points were located. In order to visualize the result, a sample frame was first used to demonstrate the k-means clustering technique.

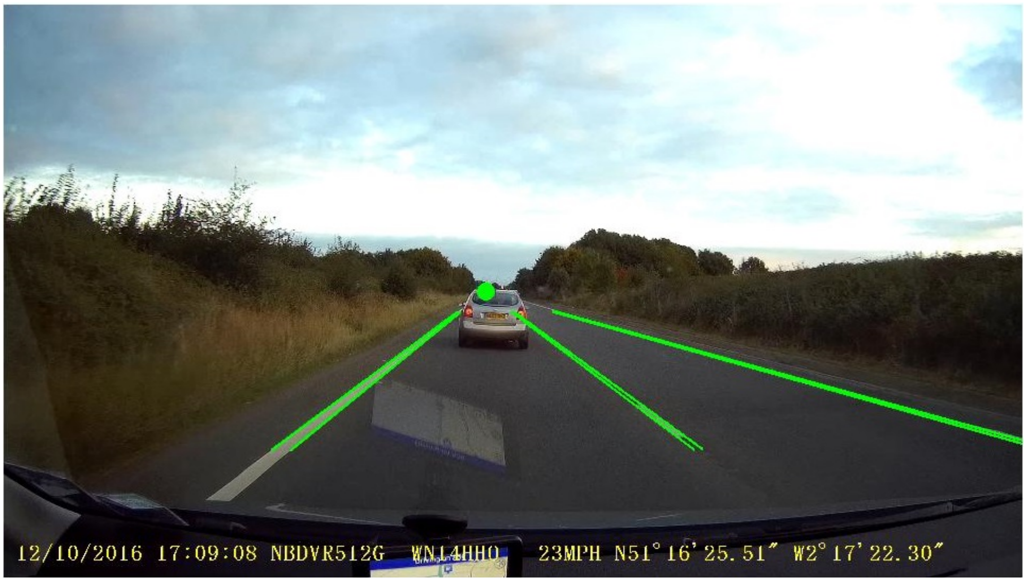


Figure 5.3. Lane markers for vanishing point detection

As shown in figure 5.3, all three lane markers are detected in this frame, and vanishing point is denoted by the green point. As six lines were detected, a sum of 15 intersections was obtained. Meanwhile, it can be noted from figure 5.4 that these intersections were divided into three clusters. While cluster 2 and cluster 3 mainly contained outliners, most intersections were in cluster 1. Therefore, as described in the previous section, the centre of cluster 1 was regarded as the vanishing point of this frame. As the geometry of the frame was nearly symmetry, the vanishing point should be roughly near the centre of the image. Therefore, the detected vanishing point position was reasonable. Moreover, as the vanishing point position should be rather consistent along the straight route, the positions in 114 frames were compared to further validate the proposed algorithm.

Figure 5.4. Vanishing point detection in one frame

As illustrated in figure 5.5, red points are the recorded vanishing points of 114 continuous frames, and the green point denotes the cluster centre of all vanishing points. Meanwhile, the intra cluster distance was computed. The accumulated distance to the cluster centre was 831.6615, and the average distance was 7.3. This variation was acceptable considering the dimension of the image (1920 × 1080). Thus, it can be noted that the proposed vanishing point detection algorithm is qualified for further application.

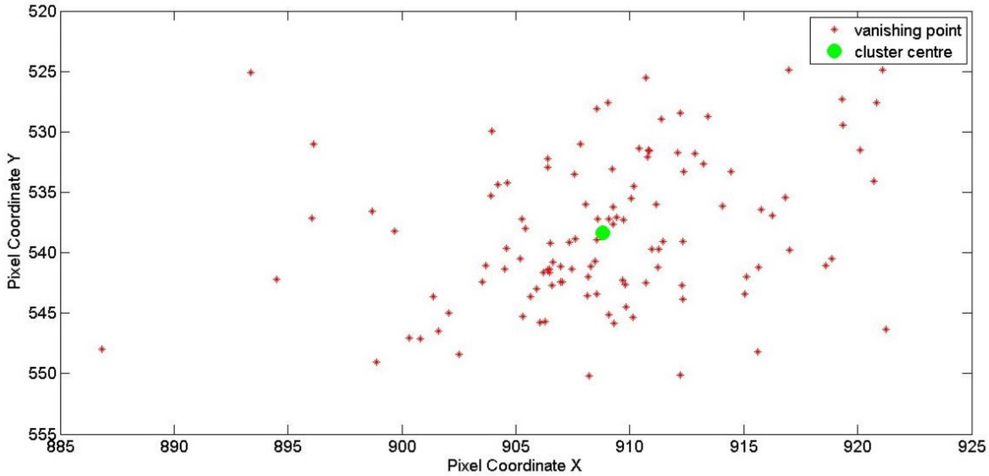


Figure 5.5. Accumulated vanishing point positions

5.2.3 Vehicle detection

With the vanishing point located in each frame, the transformation matrix between the 3D world frame and 2D image frame can be easily computed at each time step. Thus, the next procedure is to detect the leading vehicle in each frame. As vehicle type and light condition may potentially influence the detection of taillights, these two factors were examined to justify the performance of the adopted algorithm.

a b c d e f

Figure 5.6. Different type of vehicle detection

As shown in figure 5.6, two vehicle types under three weather conditions are used to validate the algorithm. The images were extracted from daily driving data. The two vehicle types were chosen as sedan and lorry, as they are the most common vehicles on road. Meanwhile, normal afternoon, foggy and rainy were adopted to investigate the influence of light condition. Figure 5.6a, 5.6b, 5.6c illustrate the sedan type of vehicle under these conditions, while figure 5.6d, 5.6e, 5.6f show the lorry type of vehicle. It was found that the proposed algorithm can sufficiently detect taillights of the leading vehicle in various weather conditions. Its robustness to vehicle type and light condition can hence be validated.

5.2.4 Distance computation

Similar to the validation of radar measurements, the accuracy of computed headway distance from dashcam needs to be examined. As estimating distance using dashcam requires a leading vehicle and lane markers, manually measure the gap distance was hence not safe and realistic. Therefore, the approaching to congestion scenario was used as an alternative option. With the leading vehicle stopped and host vehicle approaching, dashcam measurements were processed at its original frame rate, 30 Hz. Meanwhile, the host vehicle's speed profile during this period was also extracted. As the sampling rate of vehicle speed was 2 Hz, the time gaps between these samples and the complete stop were calculated. Afterwards, the headway distances at each sampling time were computed using the time gaps and the mean value of adjacent vehicle speed samples.

While this measurement was less accurate, it was sufficient for this application as dashcam data were used as relative measurements, mainly to record the changing tendency of headway distance. Therefore, this scenario was located from the video footage and corresponding data were extracted. In this scenario, the approaching to static period of the host vehicle lasted for six seconds after the leading vehicle was completely stopped. The obtained result was shown in figure 5.7.

It can be noted that although the headway distance measurements from dashcam and accumulated vehicle travel showed some deviance, the decreasing tendency matched quite well. Thus, the proposed headway estimation using dashcam is feasible, as it can be used in Kalman filter to improve continuity. Moreover, the deviance issue can also be mediated using radar measurements.

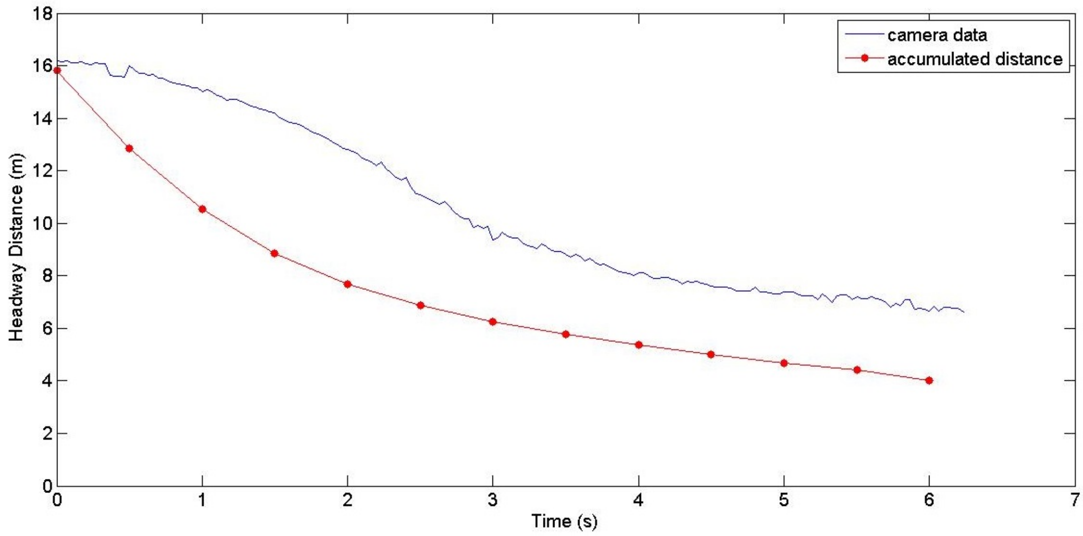


Figure 5.7. Dashcam validation

Along with the validation of the proposed algorithm, its processing speed was also evaluated. It was found that the average processing time for each frame was 0.667s during the post-processing phase. As the entire video was loaded at once for processing, which could occupy some computing memories, this processing speed was rather satisfying. With the ultimate aim of this study to be post-processing camera and radar data to achieve sensor fusion, the real-time in-vehicle performance of this algorithm has hence not been evaluated. However, it should be noted that the proposed algorithm could potentially be faster in real-time scenarios.

5.3 Correlation between radar and camera

With the radar and camera separately examined, the correlation between radar and camera needs to be assessed. This is mainly because radar measurements contain multiple objects, and the desire target is the leading vehicle. While it is difficult to directly identify the leading vehicle from radar plot, camera data can be used to isolate the same object in radar measurements. The leading vehicle position can be first computed from camera footage, and a search zone can hence be created around this detected position to find the corresponding object in radar measurements. Therefore, the correlation between radar and camera data needs to be examined. This can be achieved by plotting radar measurements on corresponding camera footage. A corresponding MATLAB function was created, and a captured frame was shown in figure 5.8.

Figure 5.8. Plotting radar objects on video footage

The two red squares denoted radar measurements at the same time step, (0,15) and (3,17) respectively. While the correlation on the oncoming vehicle was good, there was a deviance on the leading vehicle. The pixel coordinate of the converted radar plot was (958,601), and the detected leading vehicle in this frame was (927,580), leading to a pixel distance of 37.44. As this deviance was relatively small, it can be easily compensated by setting a larger search zone. Therefore, it can be noted that the correlation between radar and camera is satisfying.

5.4 Kalman filter optimisation

After examining the correlation between radar and camera, the final procedure is to apply Kalman filter to optimise the distance measurement. The purpose of this optimisation is to compensate the drawbacks of each individual sensor. For example, while the radar data is more accurate, it can lose targets in some measurement cycles. Meanwhile, camera measurements are more continuous with reduced accuracy. Therefore, Kalman filter is adopted to fuse both sensory measurements and generate optimised distance estimations.

In order to examine the performance of the established Kalman filter, the radar data and dashcam footage of a 350s journey were isolated from recorded files. This extracted trip covers a total distance of approximately 4000m, and contains three closing-in events. Thus, it could be a suitable evaluation of the filter. The separate sensory measurements and fused estimations were illustrated in figure 5.9.

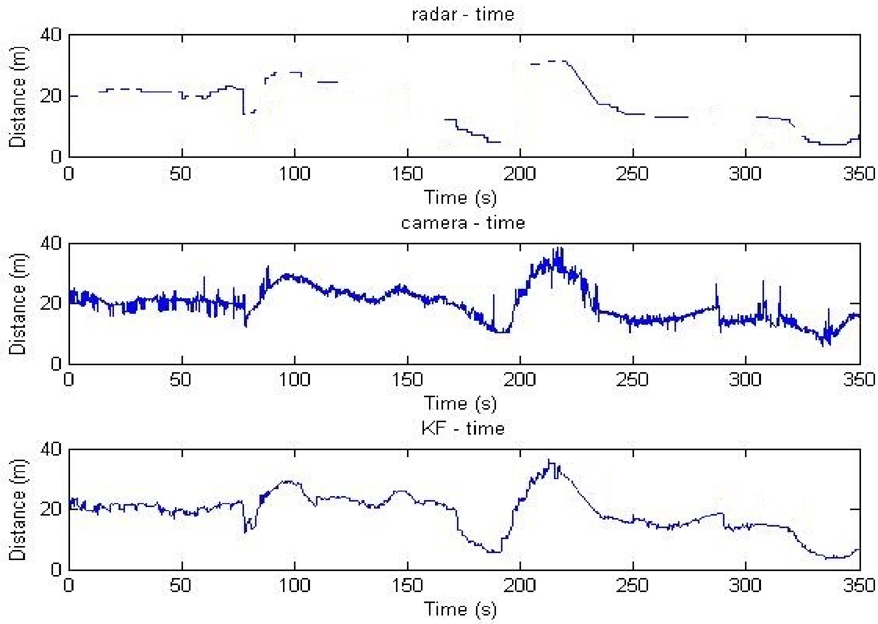


Figure 5.9. Kalman filter optimisation

It can be found from figure 5.9 that the correlations between each sensor and the Kalman filter are satisfying, as the shape of each plot is similar. Moreover, the radar measurements are smoother and more stable, which proves its accuracy. Thus, the selection of radar as an absolute measurement was justified. Meanwhile, while the continuity of camera data is commendable, it shows intense oscillations and multiple outliners. Moreover, its accuracy also deteriorates in short range. From extracted data, it was found that the average deviation from camera to radar data was 1.35m for distance larger than 10.5m, and 3.92m for short range. While both sensors have corresponding drawbacks, the performance of the established Kalman filter is promising. It can be noted that the filter's estimations show an improved continuity and reduced oscillations compared with each individual sensor. When radar went offline, the filter used its prediction model and camera measurements to improve continuity and reduce oscillations. Meanwhile, radar data were used to improve estimation accuracy when received.

5.5 Chapter summary and conclusions

The primary aim of estimating distance by fusing radar and monocular camera was achieved. The transformation matrix between camera and radar was first computed to facilitate the conversion of sensory measurements. Afterwards, the approach for computing headway distance from monocular camera footage was developed.

The established approach consists of two steps. First is to formulate the transformation matrix between image frame and world frame, and second is to detect the leading vehicle in each image. For the matrix formulation, while the fixed intrinsic parameters of the adopted dashcam were easily obtained through camera calibration, the extrinsic parameters were automatically computed at each time step to exclude the interference caused by vehicle vibration and road gradient. In order to facilitate this computation, a novel and effective detection algorithm of lane marker was first created. The vanishing point of each image can hence be located by clustering the intersections of all lane markers. Afterwards, the pitch and yaw angles of the dashcam were computed using the vanishing point position. The desired transformation matrix can hence be formulated with both intrinsic and extrinsic parameters. Meanwhile, the taillight feature was adopted to detect the leading vehicle. With the transformation matrix and pixel coordinates of the leading vehicle, the headway distance can hence be computed from the recorded video footage.

Aside from the camera data analysis, a Python based analysing tool was developed to decode the radar measurements. Afterwards, in order to locate object depicting the leading vehicle in radar measurements, a search zone was created using the position of the detected leading vehicle in camera data and the transformation matrix between both sensors. The consistency of radar measurements is also checked to exclude abrupt changes caused by interference.

Afterwards, accuracies of both sensors were first separately examined, and the influences of light condition and vehicle type on camera measurements were investigated. The correlations between both sensors were also examined, and Kalman filter was adopted to optimise distance estimations. It was found that the established system showed a strong robustness to various scenarios and the optimizing performance of Kalman filter was satisfying. Thus, the established system is sufficient for further applications.

Chapter 6 – *Driving style classification*

This chapter presents the corresponding results of the proposed driving style classification approach, as introduced in section 4.4. In order to improve the validity of the proposed method, driving data of two additional drivers were also collected using the instrumented vehicle. Driving data of a total of 12 separate trips were used to evaluate the proposed approach, with an estimated covered distance of approximately 1106 km. This chapter consists of four sections. Firstly, the driving style classification results of the three human drivers are presented. Afterwards, the correlation between classified driving style and fuel consumption and the influence of some external factors, such as weather and time of the day, are investigated. The final section includes chapter summary and conclusions.

The results shown in this chapter have been presented at the IEEE International Conference on Intelligent Transportation Engineering and published in the International Journal of Machine Learning and Computing.

6.1 Driving style classification

In order to evaluate the proposed driving style classification approach, all three drivers were requested to drive the vehicle repeatedly in similar weather condition and time of the day, which is to minimize the potential disturbances caused by these external factors. Two trip data sets of each driver were collected and classified separately. This setting can help to investigate the variations of each individual's driving style within one trip, and the consistency between different trips. Moreover, these drivers were also compared to further assess their driving style.

The speed distributions of obtained driving data are illustrated in figure 6.1, with different trip data of the same driver combined together.

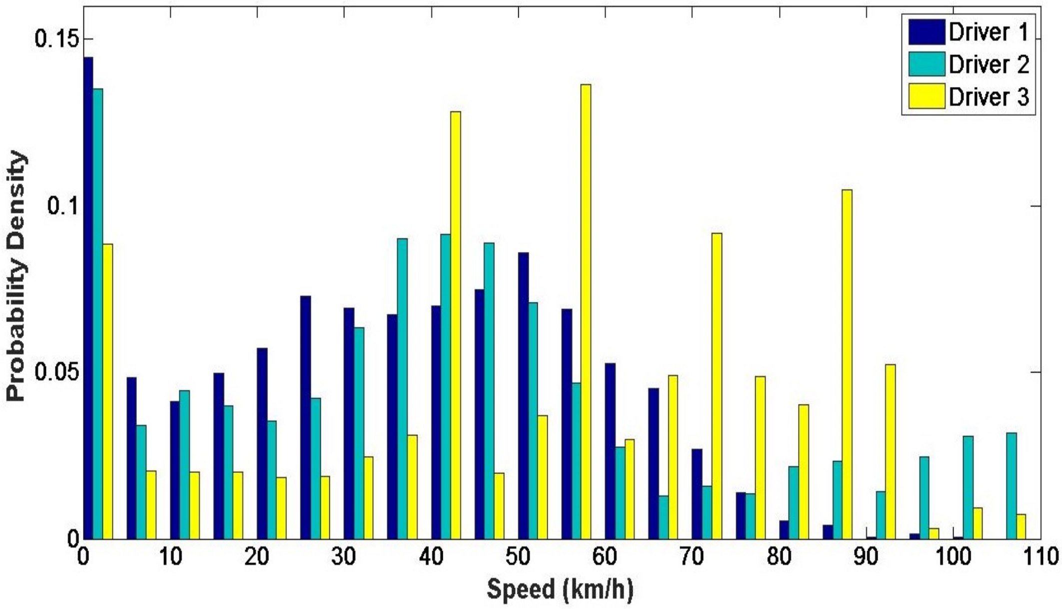


Figure 6.1. Vehicle speed distribution of each driver

As shown in figure 6.1, this histogram has a bin size of 5 km, and ranges from 0 to 110 km/h, as the maximum speeds of each driver are 100.8 km/h, 112 km/h and 106 km/h respectively. It can be noted that the speed preferences of these three drivers are distinct. The first driver shows a larger proportion (41.4%) in low speed range (0 – 30 km/h). Meanwhile, the third driver has the largest proportions at 40 – 45 km/h and 55 – 60 km/h, which are 12.8% and

13.6% respectively. Moreover, the second driver has a relatively smoother speed distribution in speed range (0 -70 km/h), and a larger proportion (17.8%) in high speed range (70 -110 km/h).

While the speed distributions of these three participants are rather distinct, it should be noted that the speed distributions of the entire journeys are shown in figure 6.1, which consists of all driving scenarios, such as car following, free flow, stop, etc. As different driving scenarios can have huge impacts on vehicle's speed, which can restrain the driver's preference, it shall be noted that these driving scenarios need to be isolated to minimize the basis introduced by this factor. As this study focuses on car-following scenarios, which can reveal both the driver's action and cognition characteristics, this type of driving scenarios was hence extracted from the recorded real driving data. Thus, it can be noted that the proposed classification approach focuses on differentiating different driving styles in the car-following regimes only. Moreover, to minimize the influence of some external factors, such as weather conditions and time of the day, the selected driving data for classification were all recorded under similar conditions of these external factors.

6.1.1 Driver 1

The classification results of the first driver are shown in table 6.1.

Table 6.1. Classification results of driver 1

Trip	Driving Style	Driving Event (%)		
		Accelerating	Braking	Maintaining
1	Aggressive	15.2	12.8	10.0
	Normal	73.4	45.8	57.9
	Defensive	11.4	41.4	32.1
2	Aggressive	21.4	3.8	14.7
	Normal	69.3	44.5	61.2
	Defensive	9.3	51.7	24.1

It can be noted that the classification results were rather consistent between two trips, which indicates that this driver possesses a relatively stable driving style. Meanwhile, this driver tends to be a normal driver, as most driving events were classified as normal driving. Moreover, the similar proportions of normal and defensive during braking events also demonstrate that driving style can vary during each trip. Therefore, this driver can be classified as a mixed normal and defensive driver, with a higher tendency towards normal driving. Based on the average of both trips' data, this driver can be defined as 13.0% aggressive, 58.7% normal and 28.3% defensive.

6.1.2 Driver 2

As shown in table 6.2, the second driver has a mixed driving style. While aggressive was the dominant driving style during accelerating events in both trips, this driver's driving style in braking and maintaining events varied dramatically, which could be caused by some external factors, such as traffic condition and tight schedule. It can be noted in the second trip that while most braking events were classified as defensive, a higher tendency of aggressive driving was detected during both accelerating and maintaining events. It demonstrates that this driver might have a tight schedule during this trip, and he still concentrated on driving safety (93.7 defensive braking). Nevertheless, this driver tends to be an aggressive driver, especially in accelerating events. From percentage perspective, this second driver can be classified as 49.5% aggressive, 29.2% normal and 21.3% defensive.

Table 6.2. Classification results of driver 2

Trip	Driving Style	Driving Event (%)		
		Accelerating	Braking	Maintaining
1	Aggressive	88.7	5.4	41.7
	Normal	0.8	86.5	56.3
	Defensive	10.5	8.1	2.0
2	Aggressive	93.6	3.6	63.8
	Normal	5.6	2.7	23.3
	Defensive	0.8	93.7	12.9

6.1.3 Driver 3

The classification results of the third driver is listed in table 6.3.

Table 6.3. Classification results of driver 3

Trip	Driving Style	Driving Event (%)		
		Accelerating	Braking	Maintaining
1	Aggressive	11.9	9.8	4.8
	Normal	30.1	2.2	43.1
	Defensive	58.0	88.0	52.1
2	Aggressive	3.2	1.4	2.3
	Normal	36.1	3.9	45.4
	Defensive	60.7	94.7	52.3

It can be noted that this driver tends to possess a mixed normal and defensive driving style. The performance of this driver was rather consistent between two trips. While defensive driving occupied a dominant proportion (88.0% and 94.7%) in braking events, both normal and defensive driving styles were detected during accelerating and maintaining events. Therefore, this driver can be classified as a mixed normal and defensive driver, with a higher tendency of defensive driving. This driver can be defined as 5.6% aggressive, 26.8% normal and 67.6% defensive.

6.1.4 Driver comparison

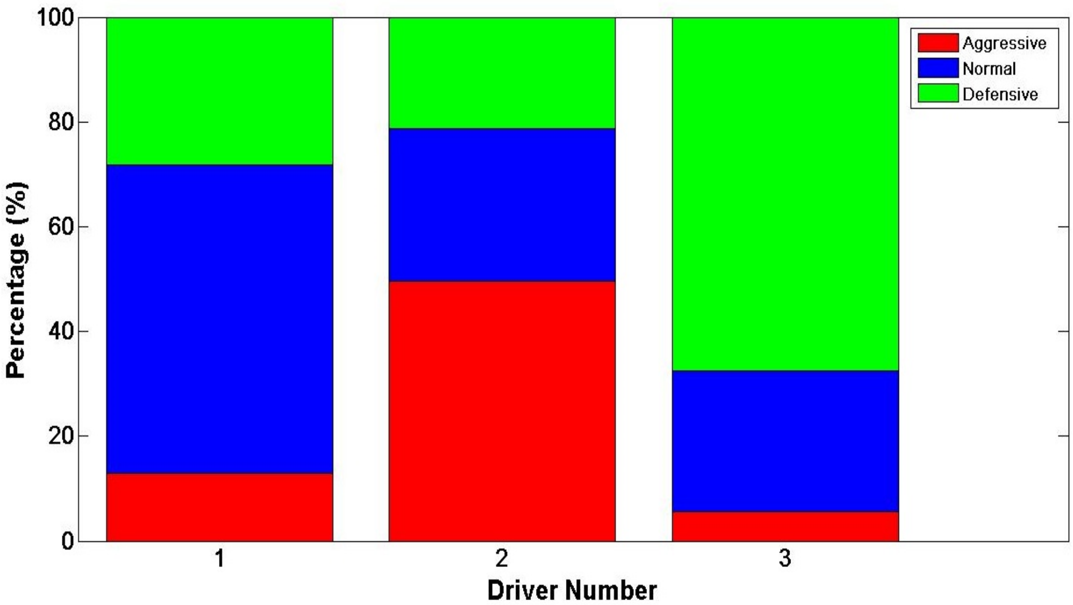


Figure 6.2. Driving style classification of three drivers

With the driving style of each driver separately classified, a cross comparison among these three drivers was performed. As illustrated in figure 6.2, while all three driving styles are detected in each driver's data, these three drivers tend to be more normal, more aggressive, and more defensive separately.

Moreover, in order to evaluate the performance of the proposed classification approach, the jerk profile of each driver was computed for validation. Defined as the rate of change in acceleration or deceleration, jerk is widely recognized as a crucial factor in determining the driver's aggressiveness (Murphey et al., 2009). While the classification with jerk only focuses on the driver's reaction on speed control, and neglects the influence of traffic condition, its validity in revealing driving style variations has been confirmed in two separate studies conducted by Murphey et al. (2009) and Lee and Oberg (2015). Therefore, the jerk profiles of each driver were computed, and the distributions of absolute jerk are shown in figure 6.3.

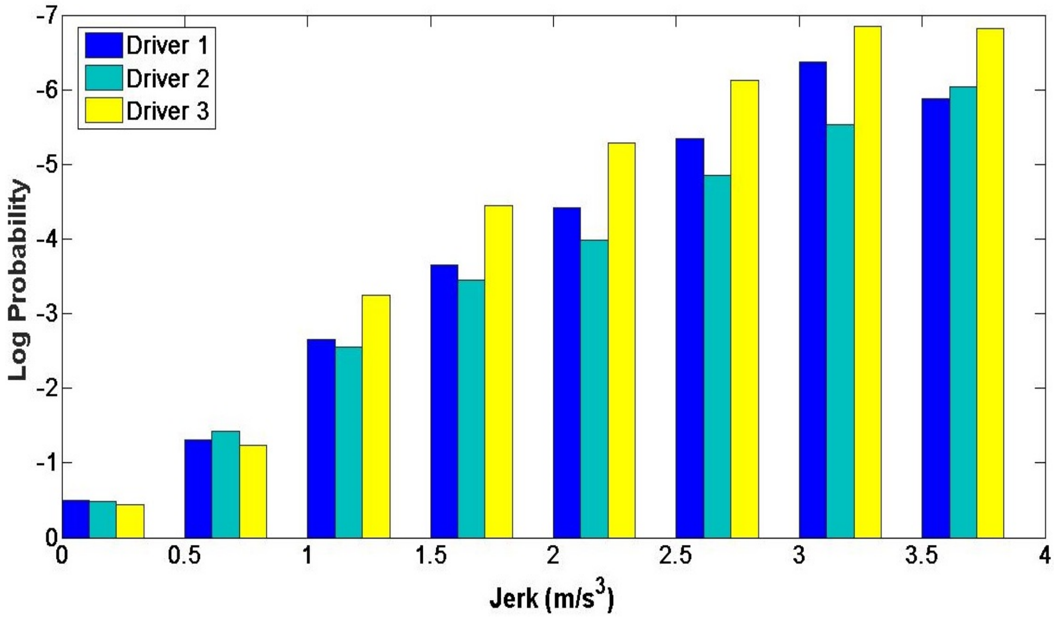


Figure 6.3. Log probability of each driver's jerk profile

It can be noted that the jerk distributions had a high correlation with the classified driving styles, especially in range [0.5, 4], where the aggressive second driver had a larger proportion in large jerk range (14.24% in [1, 4]), and the defensive third driver had a larger proportion in small jerk range (29.20%

in [0.5, 1]). Meanwhile, in range [0, 0.5], while the third driver still occupied the largest proportion (64.75%), the proportion of the second driver (61.67%) was slightly larger than the first driver (60.88%), which is contradictory to common expectations. However, it should be noted that this phenomenon might be caused by the second driver's extreme defensive behaviour during braking events. Moreover, the mean absolute jerks of these three drivers were also computed as 0.4182, 0.4561, and 0.3131 m/s^3. Therefore, based on the jerk analysis, these three drivers can be classified as normal, aggressive and defensive drivers respectively, which correspond to the proposed classification results. Thus, the performance of the proposed SVC based driving style classification approach is validated.

6.2 Correlation with fuel consumption

With the driving styles of each driver classified, their correlations with fuel consumption were also investigated. The results obtained are illustrated in figure 6.4.

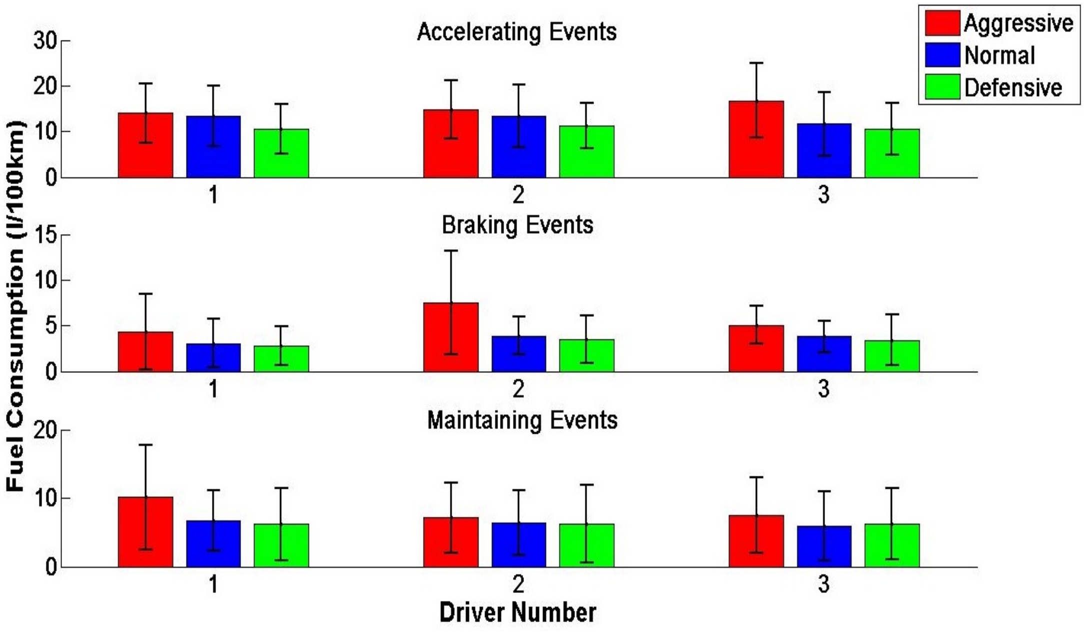


Figure 6.4. Average fuel consumption of each driver

As shown in figure 6.4, the average fuel consumption of each driver was computed for different driving styles and events. Meanwhile, the error bars were used to represent the standard deviation, which can indicate the variations of fuel consumption. It can be noted that for each separate driver, their average fuel consumption generally satisfied the common expectation that aggressive driving consumed most fuel, and defensive consumed least. Moreover, an interesting finding is that the average fuel consumption of the classified aggressive driver (driver 2) was not the largest in some driving events. For instance, in the aggressive driving part of accelerating events, the average fuel consumption of driver 2 (aggressive driver) was less than driver 3 (defensive driver). This indicates that a defensive driver can consume more fuel than an aggressive driver when driving aggressively. Nevertheless, driver 2 had a higher frequency of aggressive driving, which still led to most fuel consumed.

6.3 Weather influence

While the trip data of three drivers were recorded in the same weather condition to minimize external disturbances, six more trips of the third driver were recorded to investigate the potential influence of weather condition. The eight trips of this driver can be categorized into four pairs, each representing sunny, foggy, rainy and dark.

Table 6.4. Classification results of driver 3 in different weathers

Trip	Driving Style	Driving Event (%)		
		Accelerating	Braking	Maintaining
1	Aggressive	4.2	8.4	10.1
	Normal	75.2	40.8	82.3
	Defensive	20.6	50.8	7.6
2	Aggressive	6.9	11.4	8.2
	Normal	90.4	74.3	84.9
	Defensive	2.7	14.3	6.9
3	Aggressive	11.9	9.8	4.8
	Normal	30.1	2.2	43.1
	Defensive	58.0	88.0	52.1
4	Aggressive	3.2	1.4	2.3
	Normal	36.1	3.9	45.4

	Defensive	60.7	94.7	52.3
5	Aggressive	0.4	5.5	1.4
	Normal	96.9	3.9	3.9
	Defensive	2.7	90.6	94.7
6	Aggressive	7.3	10.4	6.0
	Normal	92.1	12.0	17.3
	Defensive	0.6	77.6	76.7
7	Aggressive	8.6	26.1	2.1
	Normal	44.6	71.1	91.4
	Defensive	46.8	2.8	6.5
8	Aggressive	10.4	28.0	5.4
	Normal	35.8	63.7	93.9
	Defensive	53.8	8.3	0.7

The classification results of these eight trips were listed in table 6.4. It can be noted that while this driver’s driving style was rather consistent between trips in the same weather, the variations caused by different weather conditions were large.

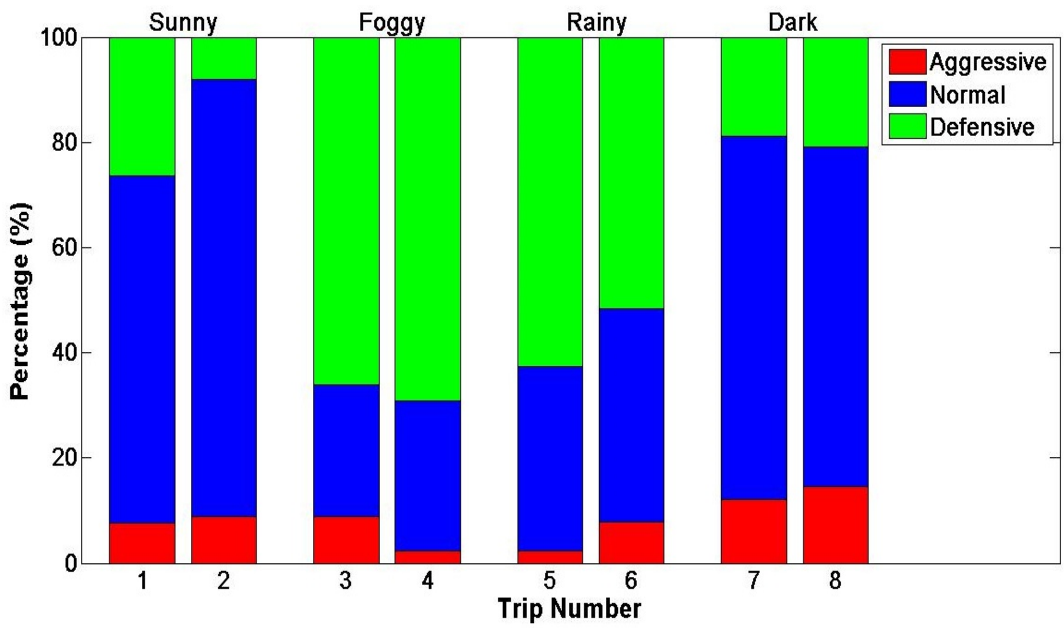


Figure 6.5. Driving style classification of each trip

As shown in figure 6.5, the driving style of this driver tended to be more normal in sunny and dark, and more defensive in foggy and rainy conditions. While the variations between sunny, foggy and rainy can be direct evidence of how weather can affect driving style, the percentage distribution of dark indicates that time of the day may also have considerable influence. This is because a major difference introduced by these three weathers (sunny, foggy and rainy) is the visibility. Meanwhile, this driver also performed more defensively with reduced visibility in foggy and rainy conditions. However, the driver showed a higher aggressiveness in dark condition, when visibility was also restricted. This indicates that the time of the day and the eager to get home may have a larger influence on driving style than weather conditions. Thus, incorporating these factors in future research may further improve the performance of driving style classification. Nevertheless, the potential influence of weather on driver's driving style is validated.

6.4 Chapter summary and conclusions

The primary aim of classifying driving style using Support Vector Clustering was achieved. During the data collection phase, 12 trip data from three drivers were collected. Both headway distance and vehicle state information were recorded to reveal the driving style variations. Afterwards, a dynamic sliding window approach was proposed to segment each trip into different event groups. During the data analysis phase, Discrete Wavelet Transform was first performed to extract spectral features of collected data. Afterwards, Principal Component Analysis was used to reduce the dimension of feature parameters, and identify prominent factors from the combined statistical and spectral features. Support Vector Clustering was then performed on these prominent factors to classify driving styles and indicate the driving pattern variations of each driver.

The performance of this proposed approach was evaluated using the collected data of three human drivers. Along with differentiating driving style variations of each driver, the validity of the classification results was also examined using the jerk profile. Moreover, the correlation between classified driving styles and fuel consumption was also investigated. Furthermore, the influence of weather condition on driving style was evaluated using extensive trip data of the third driver.

It was found that the proposed classification approach can efficiently differentiate the driving style variations during each trip, and classified driving styles have a high correlation with fuel consumption. Meanwhile, weather condition, time of the day and the driver's eagerness can also cause variations in driving style.

Therefore, it can be noted that the proposed Support Vector Clustering based driving style classification approach can effectively differentiate the variations in each individual's driving pattern. More importantly, it validates the hypothesis that each driver's driving style is not consistent and can be affected by many factors. Thus, a more complete driving style classification method that incorporates these external factors is recommended for future research.

Chapter 7 – *Driver model development and calibration*

This chapter presents the results obtained from driver modelling and calibration, together with the simulation evaluation of the established models. This chapter consists of three parts. The vehicle model is examined first as the foundation of the simulation evaluation. Afterwards, the driver models developed using the methods proposed in section 4.5 are evaluated separately. Finally, the two calibration methods and corresponding established driver models are further compared and discussed.

Parts of the results illustrated in this chapter are published in the proceedings of the International Conference on Applied Human Factors and Ergonomics, and submitted to the IEEE Transactions on Intelligent Transportation Systems.

7.1 Vehicle model validation

As outlined in section 4.6.1, a vehicle model representing the VW Sharan should be developed first to facilitate the evaluation of the established driver models. As the overarching aim of this project is to develop humanized driver models that can incorporate driving style variations into procedures that are anchored to the standard drive cycle tests, it should be worthy to first assess the vehicle model's performance with recorded actual inputs from the corresponding vehicle. Therefore, the 4WD AVL RoadSimTM 48" Chassis Dynamometer (shown in figure 7.1) and the Stähle Autopilot SAP2000 robot driver (shown in figure 7.2) within the Centre for Low Emission Vehicle Research at the University of Bath were used to acquire related experimental data. The Sharan was installed on the chassis dynamometer and the robot driver was instructed to follow the WLTC Class 3 drive cycle speed profile. The vehicle state and robot driver information were recorded using a Rebel data logger. Essential information, such as vehicle speed, throttle pedal position, gear selection, engine rpm, robot accelerator leg and brake leg movement, was extracted. While throttle pedal position, brake pedal position and gear selection were required as inputs of vehicle model, brake pedal position could not be directly recorded by the data logger. Therefore, a mitigation solution of obtaining the brake pedal position was created for this validation. As the accelerator leg and brake leg movements of the Stäle robot were also recorded, and the relation between pedal positions and leg movements should be rather fixed after installation, a cross-mapping between vehicle pedal and robot leg was hence created using throttle pedal and accelerator leg. Afterwards, the brake pedal position can hence be obtained with this established mapping and recorded brake leg movement information. Both pedal positions and gear selection were transmitted to the vehicle model as inputs, and the obtained vehicle speed profile is shown in figure 7.3, together with the corresponding experimental result and computed error.

Figure 7.1. AVL RoadSimTM 48” Chassis Dynamometer

Figure 7.2. Stähle Autopilot SAP2000

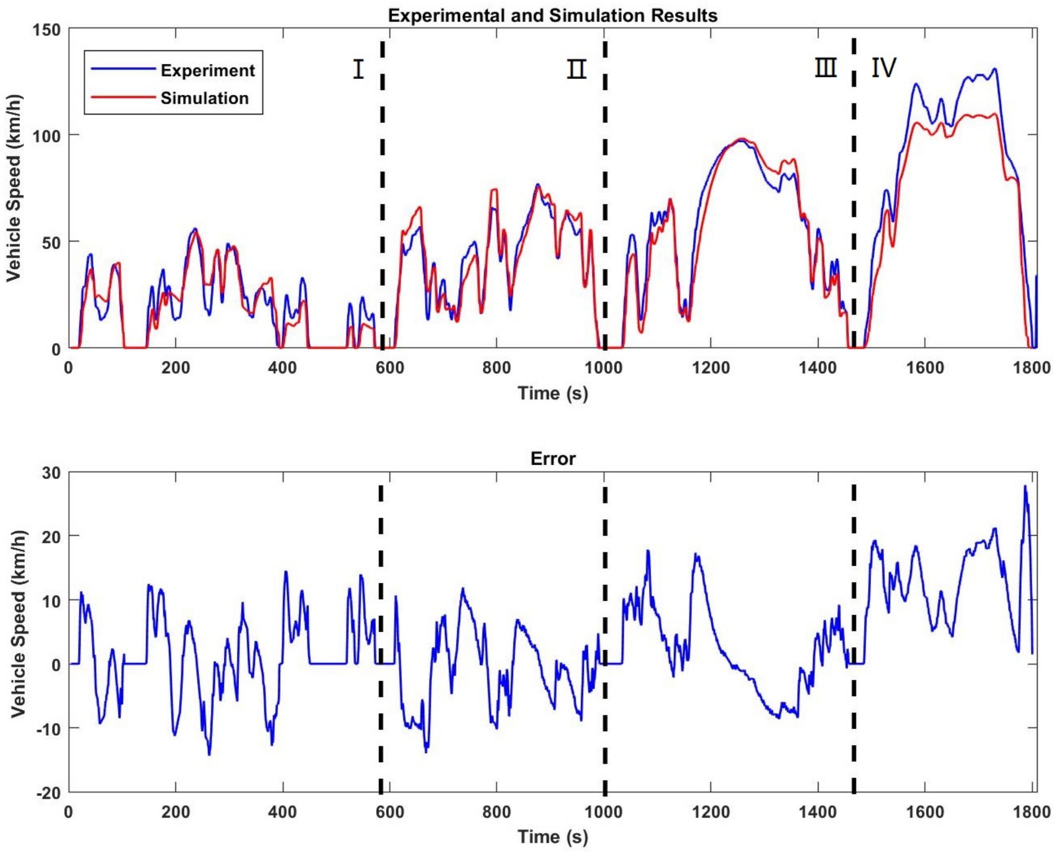


Figure 7.3. Speed comparison between simulation and experiment

While the WLTC drive cycle for a Class 3 vehicle can be divided into four parts, Low, Medium, High and Extra High speed, it can be noted from figure 7.3 that the correlations of the first three parts are satisfying. The simulation results generally possessed all the basic features of experimental data.

Table 7.1. Comparison between simulation and experiment

Category	Experiment				Simulation			
	I	II	III	IV	I	II	III	IV
Duration (s)	573	418	466	344	571	418	467	336
Stop distance (m)	140	35	42	28	145	37	45	30
Max speed (km/h)	56	77	97	131	54	76	97	110
Average speed (km/h)	19.2	40.1	60.0	86.1	23.1	39.4	57.2	67.4

As shown in table 7.1, the total duration, accumulated stop duration, maximum and average speed of simulation and experiment matched well for the first three parts. However, the maximum speed and the average speed of the Extra High speed segment of the simulation result was smaller than the experiment. While the exact cause of this problem was still unclear, it seems to be the consequence of the engine parameter settings, as the adopted Generic Engine block only allows the manipulation of a few parameters. Therefore, it can be noted that the established vehicle model was qualified for simulating the first three parts of WLTC drive cycle, and insufficient for the Extra High speed segment. However, owing to the selected route, the majority of collected real driving data was within Low-High speed segments, which indicated that the calibrated driver model was also specifically tuned for this speed range. Thus, the Extra High speed segment was discarded, and only the first three parts of the WLTC drive cycle data were selected as the speed profile of the imaginary leading vehicle.

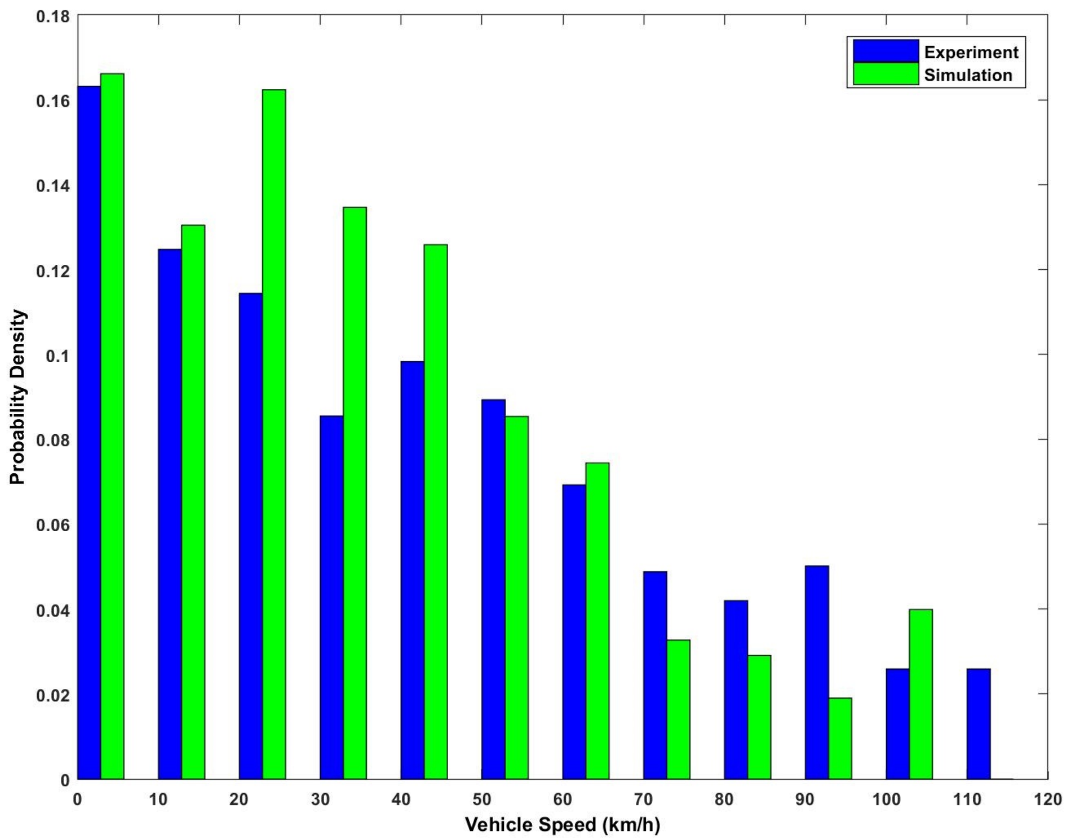


Figure 7.4. Vehicle speed histogram

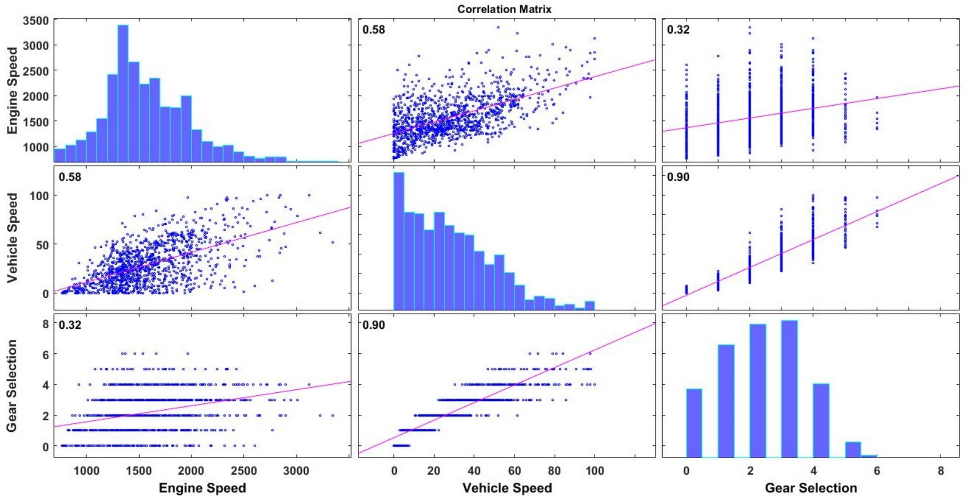
Moreover, the probability density distributions of vehicle speed for the first three parts were also computed. As illustrated in figure 7.4, it can be noted that the simulation result shows a larger proportion between 20 and 40km/h, and smaller in the speed range of 70 to 100km/h. Moreover, the largest difference occurred at speed between 110 and 120km/h. This is coincidence with the fact that the established vehicle model has a deficiency in simulating the high speed range. Despite this drawback, the probability density distributions of experimental and simulated results share similar essential features and general shape, with the largest difference to be 0.06. Thus, this model was hence capable of examining the developed driver model, as the performance was satisfying in the first three speed segments.

7.2 Driver model evaluation

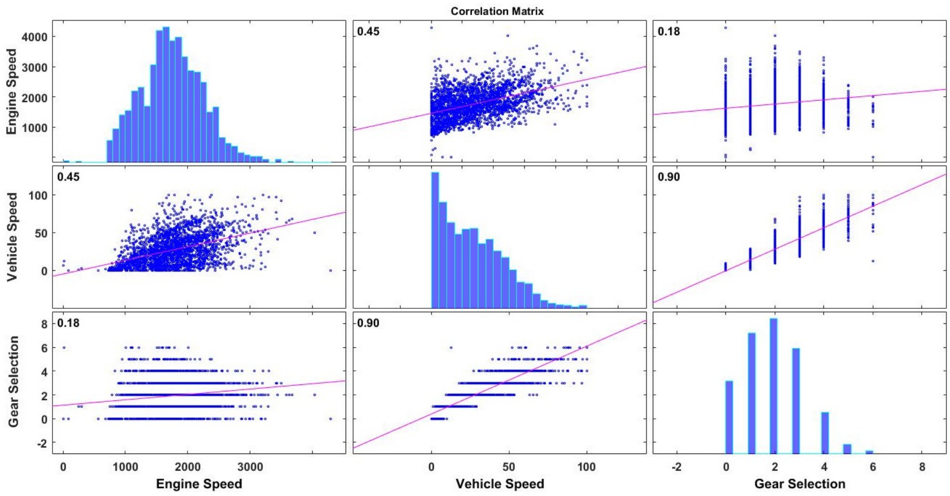
After validating the performance and accuracy of the established vehicle model, the calibrated driver models can hence be examined using the proposed the simulation scenario. Corresponding Simulink components of the driver models were developed and connected with the rest of simulation blocks. As the vehicle model performed well in Low, Medium and High speed segments, speed profiles of these three parts were hence transmitted to the leading vehicle. Thus, the total simulation time was set to 1460s. Meanwhile, an initial gap of 2m was also assigned between the leading and host vehicle. Moreover, in order to increase the similarity to human drivers and boost simulation speed, a pedal change delay of 0.5s was also introduced to the system, to simulate the common cognitive delay time of human drivers (Cole, 2012).

7.2.1 Gear shifting strategy

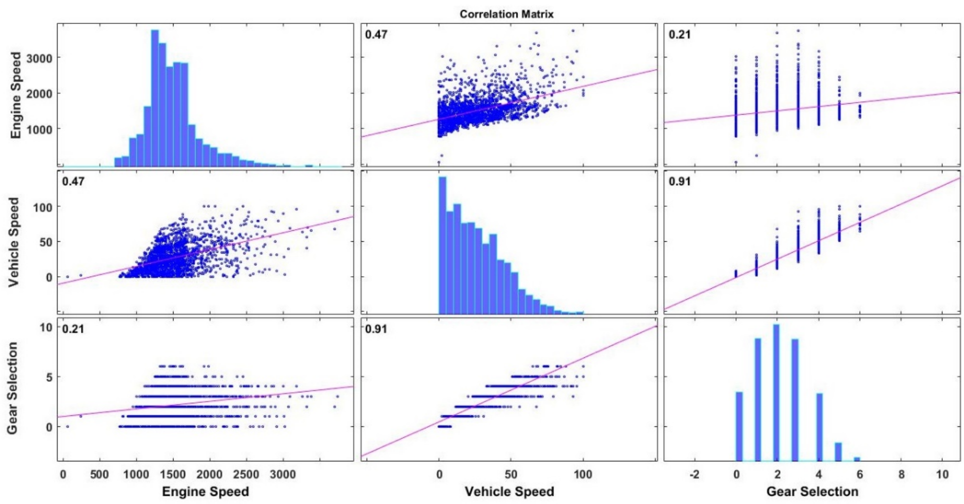
As described in section 4.5.4, Pearson's correlation coefficients were computed first to evaluate the influence of vehicle speed and engine speed on gear selection. The obtained results of three human drivers are illustrated in figure 7.5.



(a) Correlation matrix of driver 1



(b) Correlation matrix of driver 2

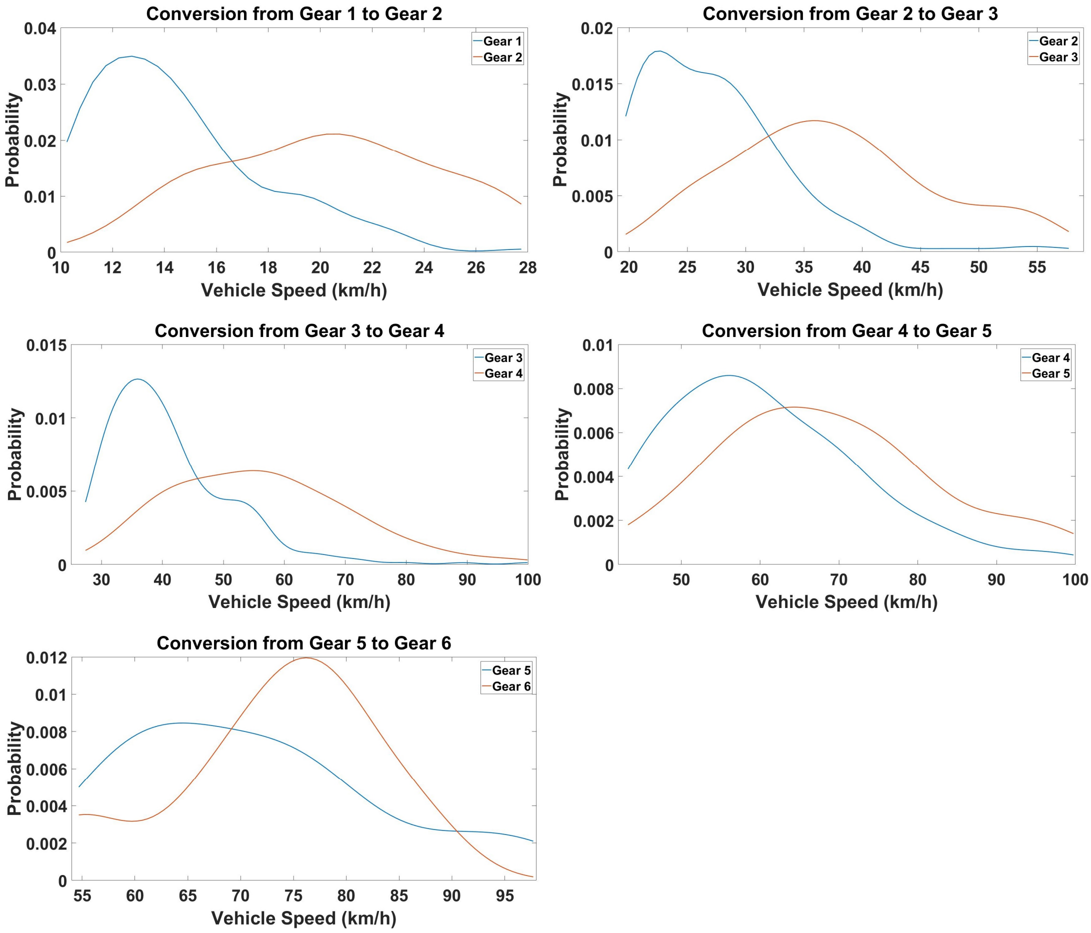


(c) Correlation matrix of driver 3

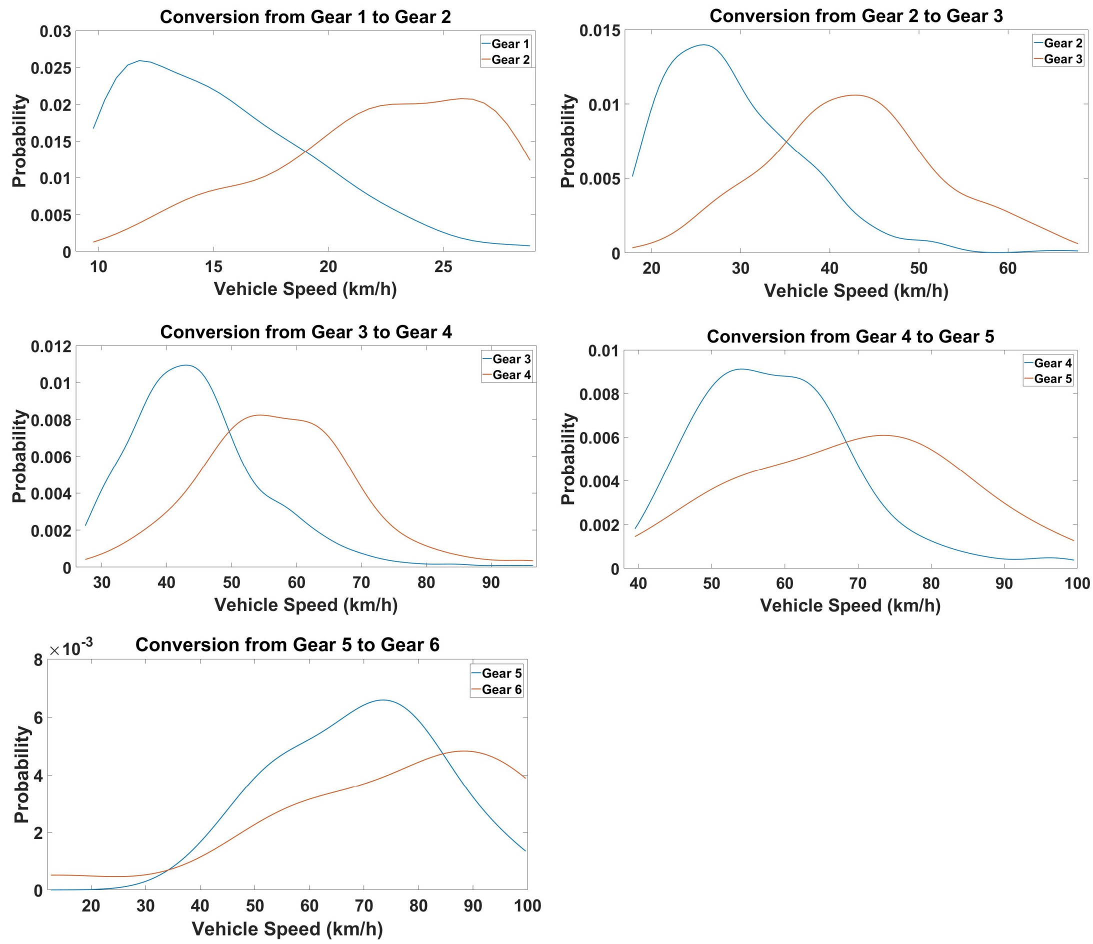
Figure 7.5. Correlation matrixes of three human drivers

It can be noted from figure 7.5 that the correlation coefficients between vehicle speed and gear selection are over 0.9 for all three drivers, indicating that the gear shifting strategies of all participated drivers are based on vehicle speed. Therefore, the thresholds in vehicle speed can be adopted to determine the transit between different gears.

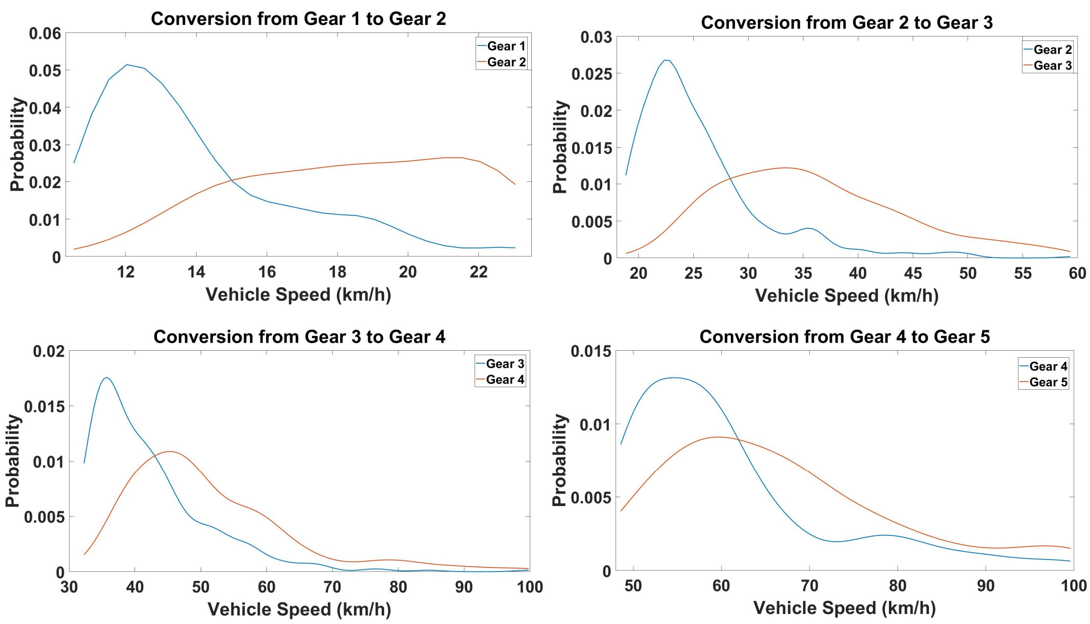
In order to determine the transit thresholds, the vehicle speed intersection ranges of each adjacent gear selections were first extracted from the collected real driving data. Afterwards, the probabilities of gear selections in each intersection segments were accumulated. Kernel distributions were then used to fit the probability distribution to the data. Finally, the intersection point of the fitted curves was adopted to determine the transit threshold. The obtained results of each driver are shown in figure 7.6.

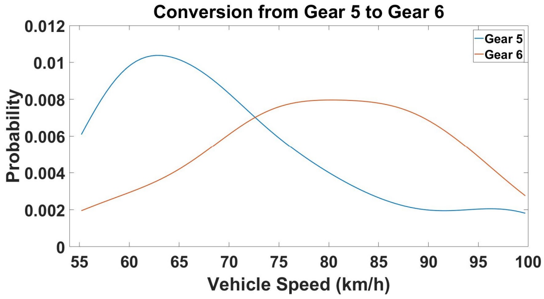


(a) Gear shifting of driver 1



(b) Gear shifting of driver 2





(c) Gear shifting of driver 3

Figure 7.6. Fitted probability distributions for gear shifting

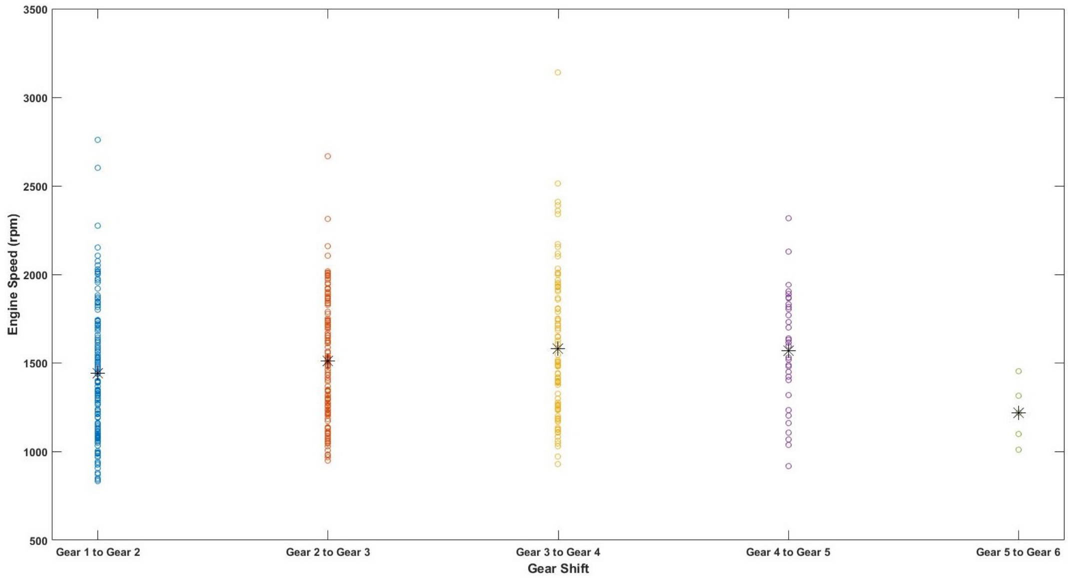
As illustrated in figure 7.6, it can be noted that the probability distributions of gear selection vary significantly among these three drivers. The corresponding vehicle speed values of the intersection points are listed in table 7.2. These intersection values were rounded to the nearest integer, as smaller changes are difficult to be perceived by human drivers.

Table 7.2. Transit vehicle speeds at gear shifting

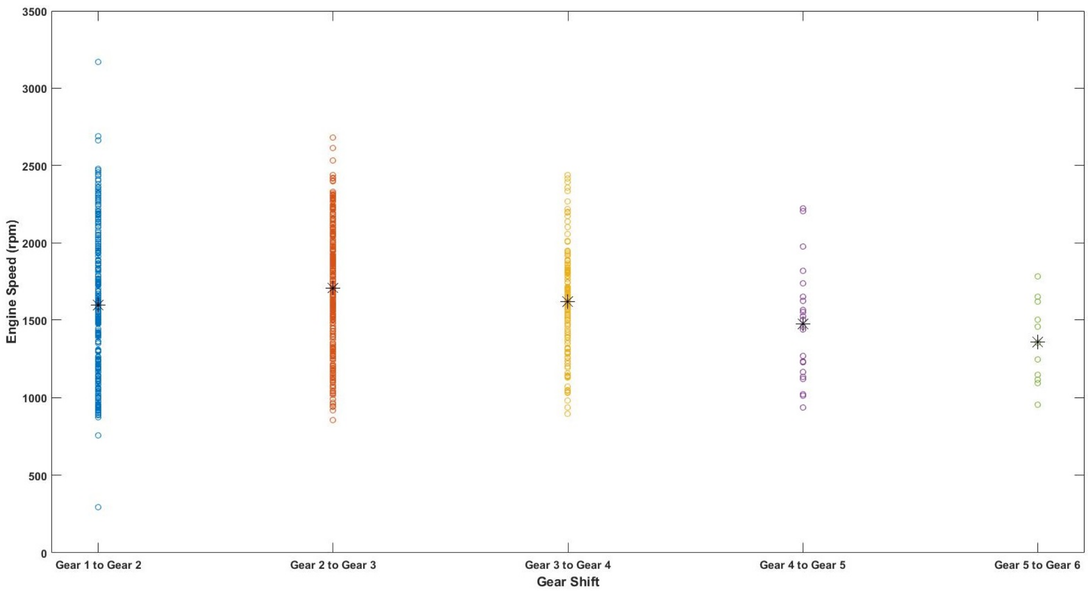
Driver ID	1->2	2->3	3->4	4->5	5->6
1	17	32	46	63	69
2	19	35	50	68	84
3	15	28	43	62	73

It can be noted from table 7.2 that there is a general changing tendency of transit vehicle speeds at gear shifting points among the three drivers. The first driver, who has been classified as the normal driver in the previous chapter, has the medium vehicle speeds for gear shifting. Meanwhile, the aggressive second driver tends to shift gear at higher speeds, and the defensive third driver prefers to perform gear shifting at an early stage. While there is one exception occurred at shifting from gear 5 to gear 6, it is mainly caused by the lack of sufficient data, as shifting into gear 6 is rather rare in the collected driving data.

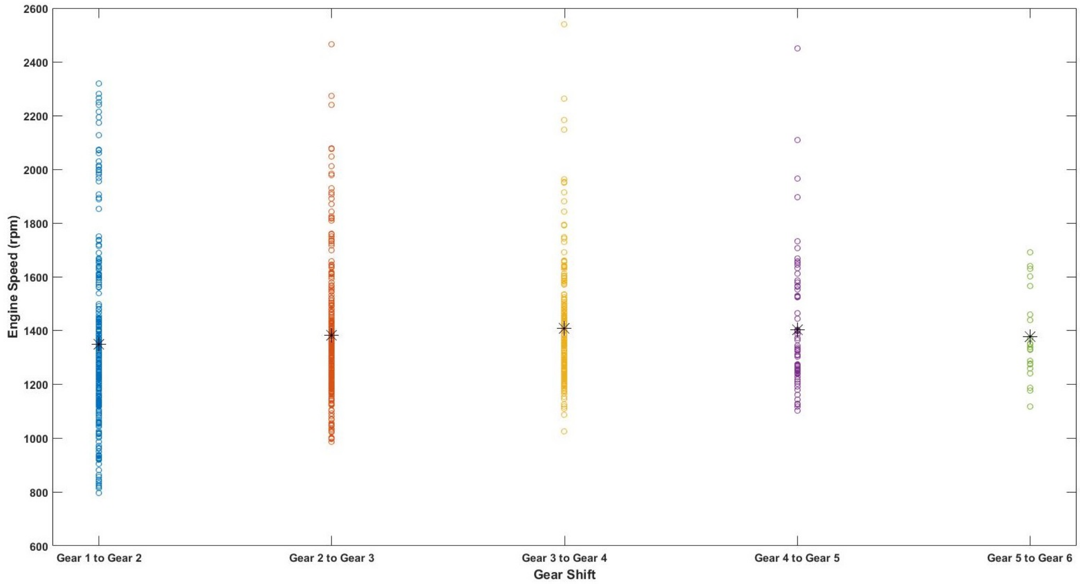
Meanwhile, it should be noted that given a fixed gear selection, the positive correlation between vehicle speed and engine speed would cause more fuel consumed when shifting into higher gear at late stage. In order to investigate into this issue, the engine speeds at gear shifting points of each driver were extracted, and the cluster centre was computed for each gear shifting point, as illustrated in figure 7.7. It can be noted from figure 7.7 that the engine speed at each gear shifting point varies significantly, which can hence explain the relatively small correlation coefficients between them, as shown in figure 7.5. While this low correlation shows that engine speed is not the underlying cause for gear shifting behaviour, the corresponding engine speed at gear shifting can reveal the fuel consumption tendency.



(a) Engine speed at gear shifting of driver 1



(b) Engine speed at gear shifting of driver 2



(c) Engine speed at gear shifting of driver 3

Figure 7.7. Engine rpm at gear shifting point

In order to further investigate into this tendency, the cluster centres of each gear shifting points were computed using K-means clustering. The clustering results are listed in table 7.3.

Table 7.3. Transit engine speed for gear shifting

Driver ID	1->2	2->3	3->4	4->5	5->6
1	1440	1509	1579	1568	1218
2	1596	1708	1615	1473	1356
3	1347	1381	1407	1401	1376

It should be noted that the obtained transit engine speeds also show the similar tendency, especially among lower gears. This trend could be caused by the characteristics of certain driving style types, as aggressive drivers tend to be sensation-seeking, and are always fond of the engine roaring sound. Moreover, high engine speed at lower gears can lead to larger output torque of the engine, and can hence increase the drivers' sense of power, which is another typical characteristic of aggressive drivers. Owing to the close linkage between engine speed and fuel consumption, it can be noted that the revealed changing tendency in engine speed confirms the potential connections between driving style and fuel consumption. Therefore, the significance of this proposed study that aiming to investigate the influence of driving style on fuel consumption can hence be validated.

7.2.2 Driver model I

Following the calibration method proposed in section 4.5.2, the membership function of the normal driver model was obtained first, as shown in figure 7.8.

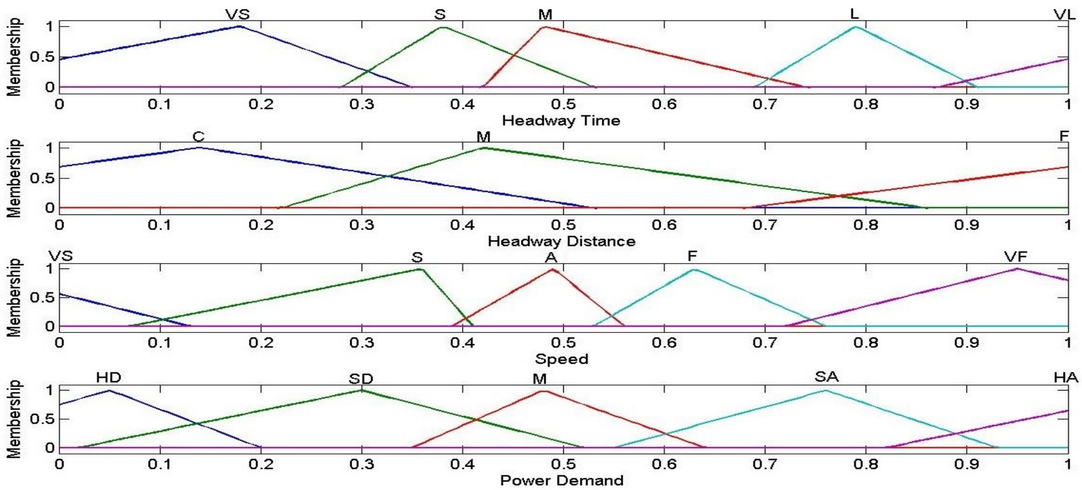


Figure 7.8. Calibrated membership functions of normal driver

In order to improve the simulation speed, this driver model was programmed as an s-function block. This setting can effectively reduce the consumed compiling time of the entire simulation model. Moreover, it can be noted that for the two headway measurements, the test driver shows wider cognition of short range, which indicates the tendency of maintaining medium or long headway distance. Meanwhile, the driver also favours driving at medium speed, and has a wider recognition of very fast speed. As for the power demand, slight decelerate and slight accelerate cover the widest cognition zone. Thus, the driver prefers to change vehicle speed mildly and generally avoids harsh acceleration and deceleration. This calibration result indicated that the test driver possessed a normal to defensive driving style, which also coincided with the driver's self-assessment and classification results.

After running the simulation, the results of this calibrated normal driver model are obtained, as illustrated in figure 7.9 and figure 7.10.

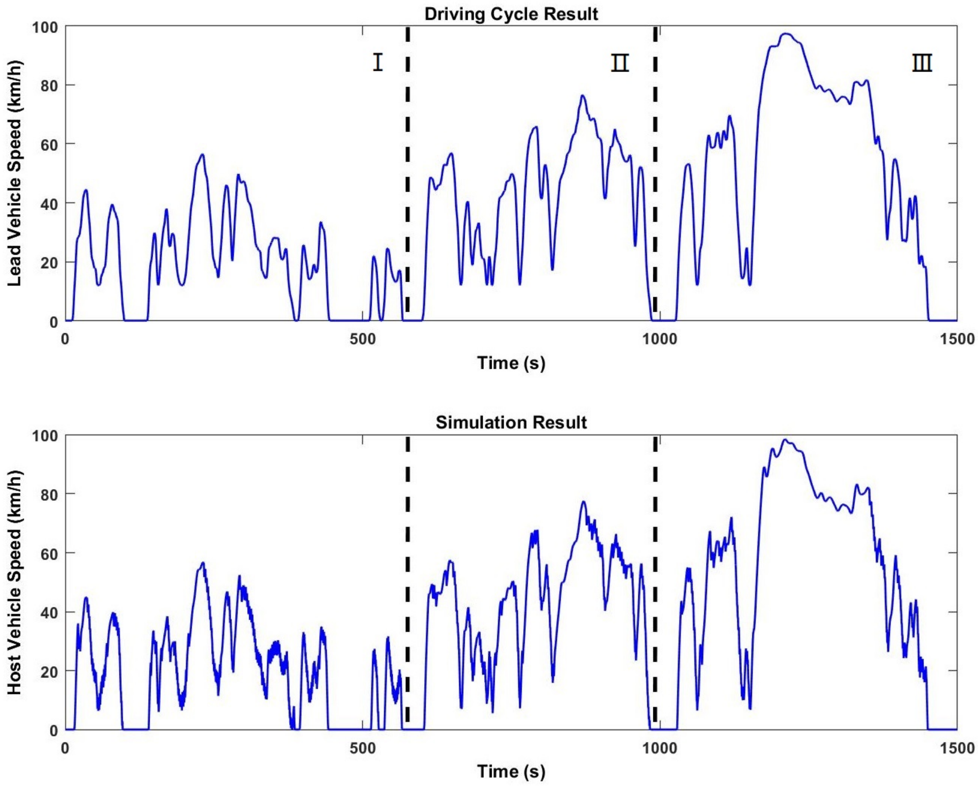


Figure 7.9. Speed comparison between drive cycle and simulation

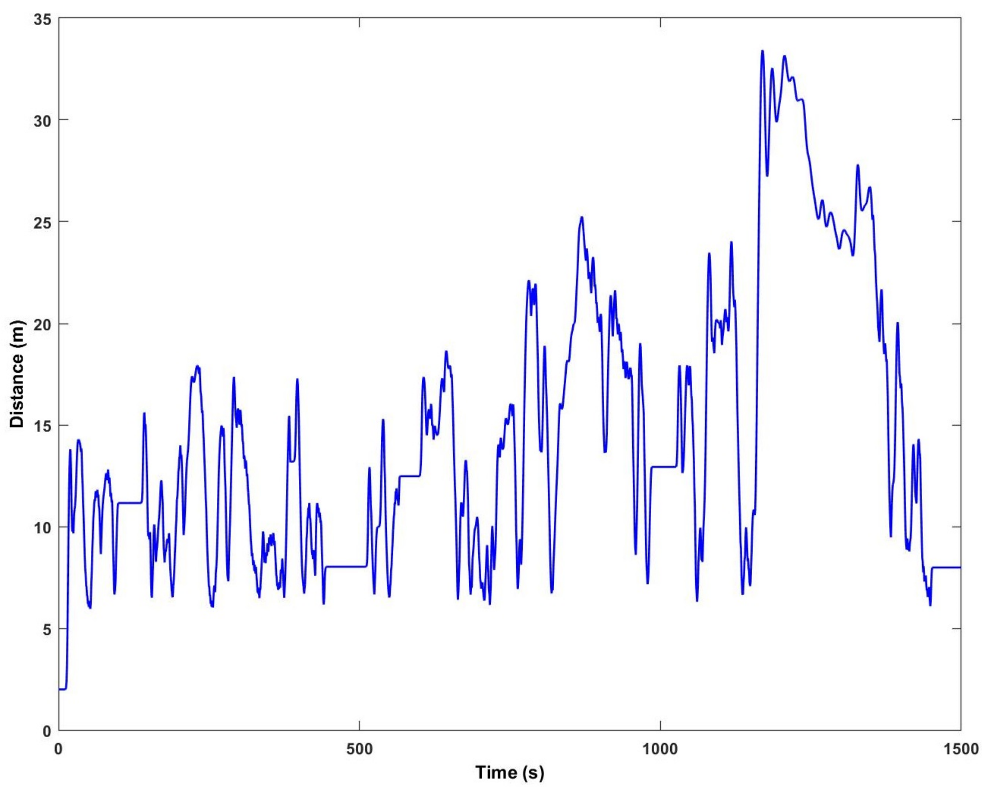


Figure 7.10. Headway distance between leading and host vehicle

As shown in figure 7.9, although the speed profile varies from WLTC drive cycle, the basic features and tendencies are preserved. It can be noted that the driver model shows some oscillations, which were introduced by the 0.5s pedal change delay. Meanwhile, the headway distance data illustrated in figure 7.10 show that the driver model was capable of performing a proper car-following behaviour, with the mean and maximum headway distance to be 12.50m and 33.42m respectively.

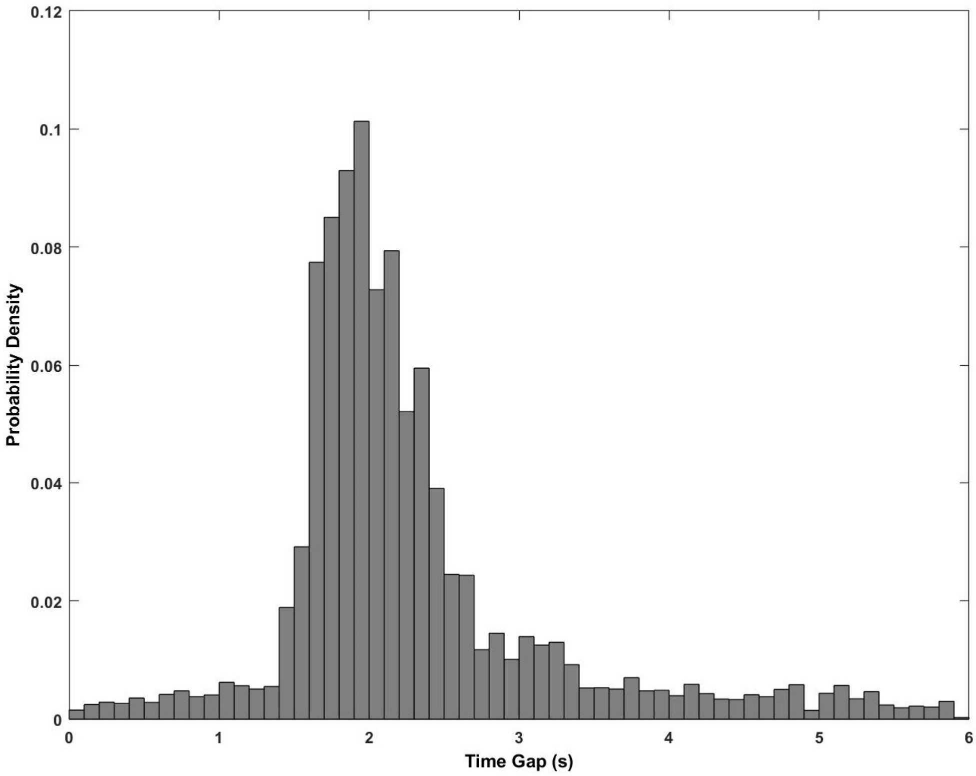


Figure 7.11. Time gap of simulation result

Meanwhile, as this driver model was calibrated using real driving data, the validity of the calibration needs to be examined. Thus, the probability density distribution of time gap during the simulation was computed and illustrated in figure 7.11. The largest proportion was between 1.7s and 2.4s, occupying 62.03 percent. Meanwhile, the weighed mean value of the accumulated time gap was 2.237s. As the average time gap of the collected real driving data was 2.141s, it can be noted that the established driver model possessed the basic features of the test driver. Thus, the calibration of membership function was satisfying.

Furthermore, in order to validate the performance of the established fuzzy logic controller in simulating human driving style, a traditional PID based driver model was also developed and tested in the same simulation scenario. As the calibrated fuzzy logic driver model can be classified as a normal driver and generally maintains the 2s time gap, the PID driver model was hence designed to also hew to the same time gap and follow a leading vehicle performing WLTC drive cycle. As a direct measure of driver's intention, throttle pedal demand was hence selected to compare the difference between the human driver and two simulation models. Meanwhile, the recorded throttle pedal positions of ten journeys along the same route of the driver were averaged to reduce any potential basis in a single trip. The obtained probability density distribution of throttle pedal position of the collected real driving data and pedal demands from both models are illustrated in figure 7.12.

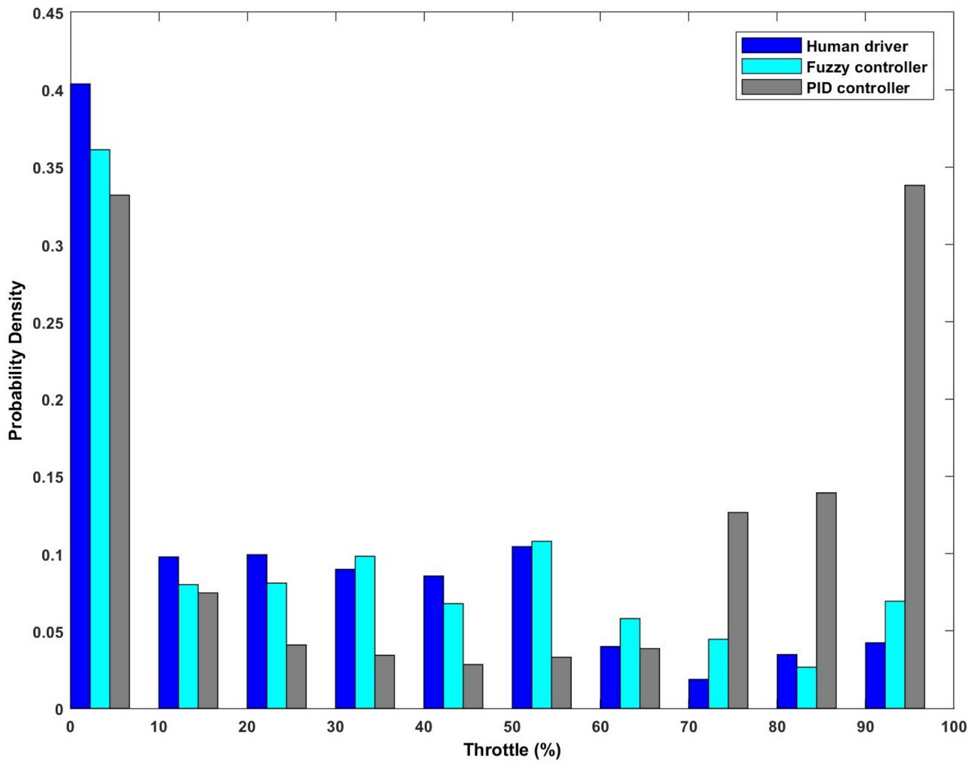


Figure 7.12. Throttle pedal comparison

As shown in figure 7.12, it can be noted that the variations of throttle pedal distribution between the human driver and fuzzy controller are much smaller than the difference between human driver and PID controller. The PID controller possessed a higher proportion of throttle value between 70% and 100%, which indicated that the PID controller accelerated harsher to maintain the required time gap. Although the human driver had a larger proportion for smaller throttle value, this may be mainly caused by complex traffic condition and repeated stop-start scenarios. Aside from this segment, the probability distribution of the human driver and fuzzy controller between 10% and 100% was much similar, with the largest difference to be 0.05, which occurred between 20% and 30%. From the distribution of probability density of throttle demands, it can be noted that the established fuzzy logic controller shows a better performance in simulating the human driver.

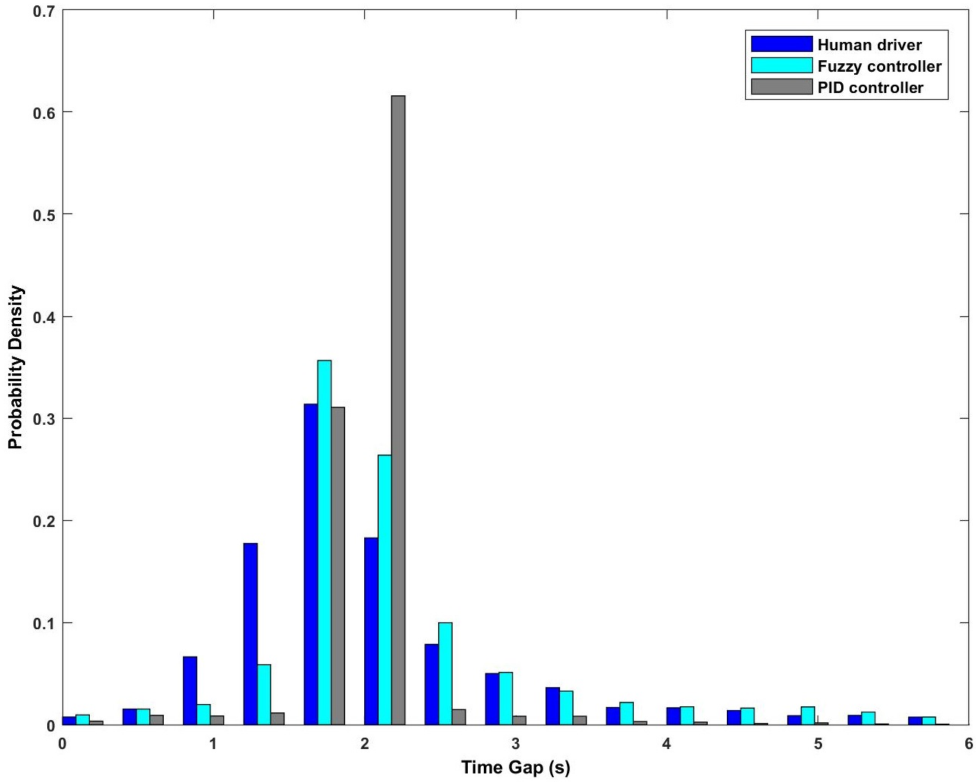
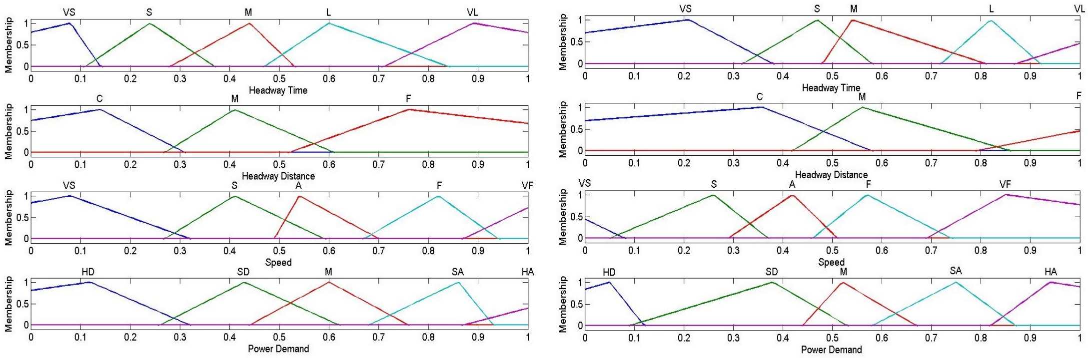


Figure 7.13. Time gap comparison

Moreover, the time gap distribution was also extracted and illustrated in figure 7.13. The intervals were increased to 0.4s for better visualization. It can be noted that the human driver shows a larger proportion of smaller time gaps, which is similar to the throttle pedal distribution and could be the consequence of complex traffic scenarios. Although there were some variations between the time gap distribution of the fuzzy controller and human driver, the established fuzzy controller still outperformed PID controller.

Aside from this calibrated normal driver model, two more driving styles were derived through modifying membership functions of the fuzzy controller. Real driving data of another two human drivers were collected using the instrumented vehicle. As classified in chapter 6, driving styles of these two drivers can be classified as more aggressive and more defensive respectively. The same tuning approach was adopted to compute the membership functions of each variable. The obtained membership functions are illustrated in figure 7.14.



(a) Aggressive model **(b) Defensive model**

Figure 7.14. Membership functions of aggressive and defensive driver

According to Meiring and Myburgh (2015), Aggressive driving style, or referred to as sporty, hostile or angry driving style occasionally, is a behavioural pattern containing risky speeding, abrupt speed change, harsh acceleration and deceleration, and improper lateral position maintenance. Meanwhile, defensive driving is defined as the contrary to aggressive driving, which generally refers to moderate acceleration and deceleration, well-maintained headway distance and careful participation in traffic flow (Tzirakis and Zannikos, 2007). It has a high correlation with normal driving with a more passive manner. It can be noted from figure 7.14 that the aggressive driver favours smaller safety distance and faster car-following speed, while the defensive driver possesses the opposite trend. For example, when headway time is 0.5, it will be perceived by the aggressive driver as a combination of

"Middle" and "Large", and defensive driver as "Small" and "Middle", which reflects the cognitive difference of these driving styles. In order to evaluate these driving styles and investigate their correlation with fuel consumption, both calibrated driver models were also examined in the simulation scenario.

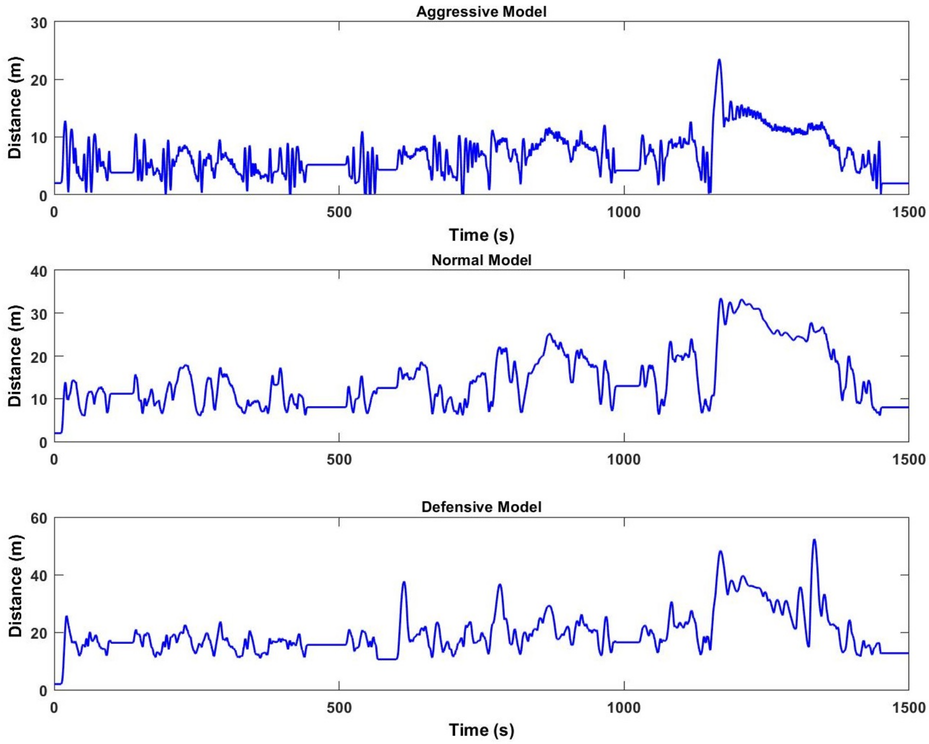


Figure 7.15. Headway distance comparison of three driver models

As shown in figure 7.15, the headway distances vary among these three styles. It was found that the mean and maximum headway gaps were 6.76m and 23.52m for the aggressive model, 12.50m and 33.42m for the normal model, and 17.94m and 52.46m for the defensive model. Thus, it can be noted that the aggressive model showed a greater tendency of tailgating, while the defensive model remained the largest safe distance. Moreover, in order to further evaluate this tendency, the headway distance distributions of each driver model were computed and illustrated in figure 7.16. It can be noted that the aggressive model is more distributed (82.5%) in small headway distance zone (0 – 10m), while the defensive model occupies the largest proportion (76.9%) for headway gap larger than 15m. This revealed variation of headway distance is in coincidence with the common definitions of these three driving styles, as headway gap is a crucial measure of aggressivity.

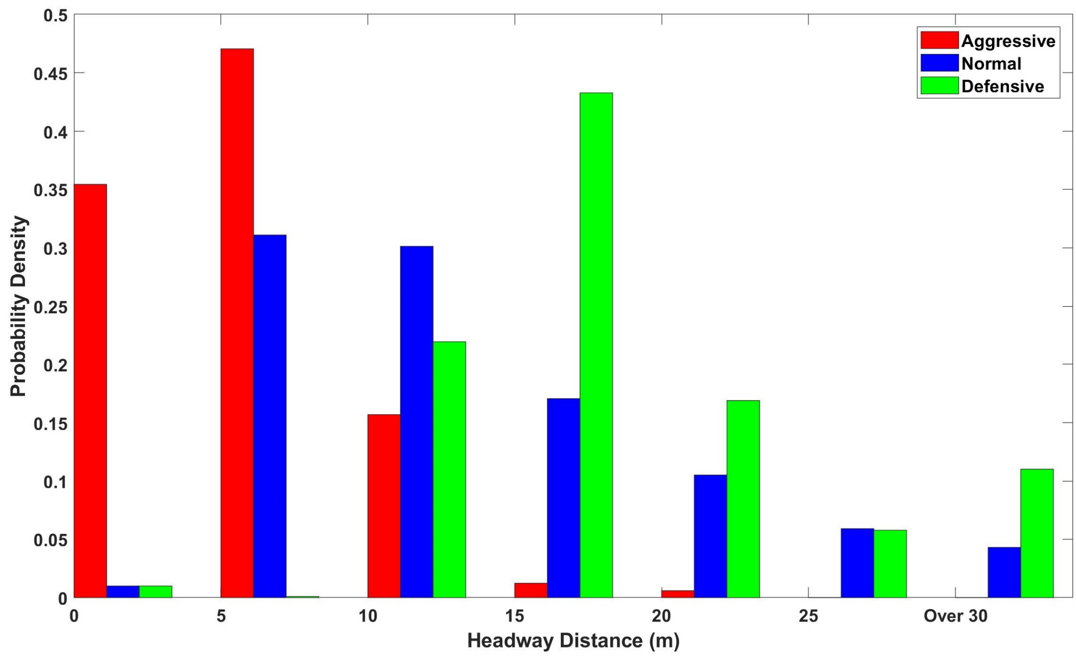


Figure 7.16. Headway distance distribution of three driver models

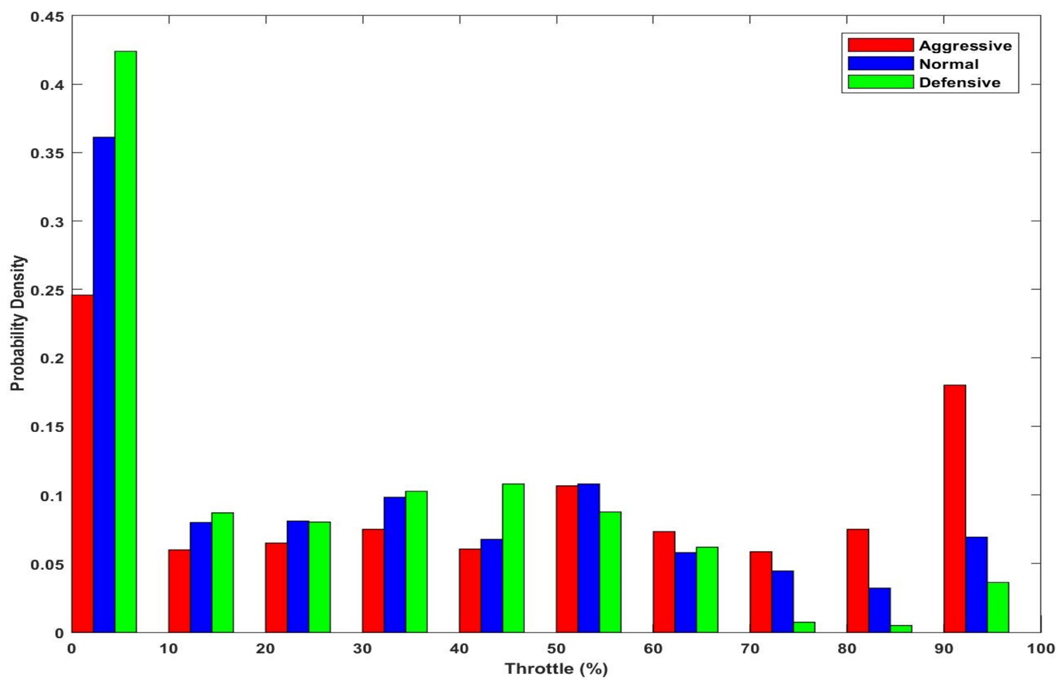


Figure 7.17. Throttle pedal demand comparison of three driver models

Meanwhile, the probability density distributions of throttle pedal demands were also selected to investigate the difference between three driving styles, as it can directly reveal the driver's intention. From figure 7.17, it can be noted that the defensive model possesses a larger proportion of smaller throttle demands, while the aggressive model shows a greater tendency of harsh acceleration. Meanwhile, the probability density of the calibrated normal model was almost equally distributed, with a smaller proportion between 70% and 90%. Although the changing tendencies of probability density among three driving styles were not consistent within some throttle segments, it can be noted that the aggressive driving shows a preference of larger throttle values, and hence harsher accelerations. Moreover, as jerk was also widely used for driving style classification (Murphey et al., 2009), the average jerks of these three models were hence computed using the corresponding speed profiles to further validate these three relative driving style models, and they were normalized using the jerk of the WLTC drive cycle. The normalized jerk values for aggressive, normal and defensive models were 2.1343, 1.2237 and 0.9046 respectively. As a larger jerk denotes harsher accelerations and decelerations, the obtained results also demonstrated the modelling of three relative driving styles was successful.

7.2.3 Driver model II

After the evaluation of the driver models developed using the first calibration approach, another three driver models were also obtained following the calibration method ANFIS proposed in section 4.5.3. As this type of driver models are directly generated and estimated from the collected real driving data, they are more robust than the previous models, and have lower demand on the relevant expert knowledge and self-assessment of the corresponding human drivers. Moreover, as additional inputs can dramatically increase the complexity of the ANFIS architecture, and the influence of the incorporation of time headway as an input parameter on the ANFIS was not prominent, only vehicle speed, pedal position, and distance-based headway were adopted for the modelling. Through feeding the pre-processed real driving data to the established ANFIS system, three corresponding driver models were obtained. The tuned membership functions of these driver models are illustrated in figure 7.18.

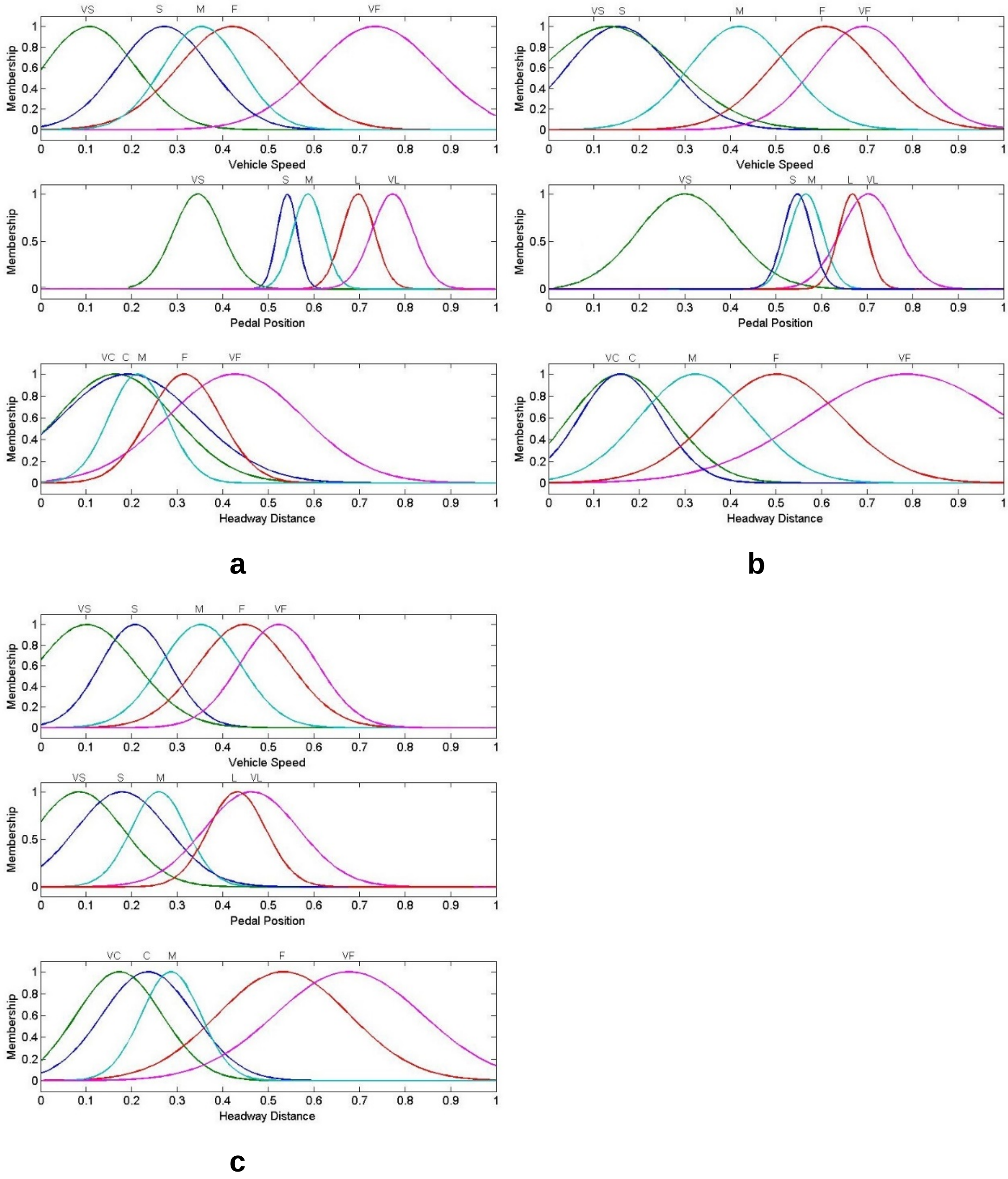


Figure 7.18. Tuned membership functions of three driver models

Following the driving style classification results in chapter 6, the collected real driving data were used to calibrate the aggressive driver model (figure 7.18a), the normal driver model (figure 7.18b), and the defensive driver model (figure 7.18c). It can be noted from figure 7.18 that the tuned membership functions vary significantly among the established three driver models. As shown in figure 7.18, the first model's membership functions of vehicle speed and pedal position are more located to the right, while headway distance more to the left.

This phenomenon indicates that the first driver model tends to be more aggressive as it has a higher cognition level of fast speed and large pedal position, and a lower level of large headway gap. Similarly, the third model tends to be more defensive with the opposite trends of membership functions. Meanwhile, the second model can be regarded as a normal driver comparing with the other two models. This initial finding coincides with the driving style classification results, which improves the validity of the tuning results. Moreover, in order to evaluate the tuning performance of the established models, the RMSE was adopted to compute the difference between data and ANFIS output. The final RMSE were 0.1011, 0.0794, and 0.0856 respectively. Thus, it can be noted that the tuned driver models possess the driving styles of human participants.

With the driver models calibrated, they were then connected to the vehicle model to evaluate their difference in the proposed car-following simulation scenario. The headway distance and throttle pedal position were selected as the prominent factors to reveal the variations.

From figure 7.19, it can be noted that the established driver models have different headway distance profiles. While their basic shapes were similar, the average headway gaps were computed as 17.7m, 18.7m and 20.4m respectively. This finding correlates with the common definitions of these driving styles, as aggressive drivers are more likely to tailgate, and defensive drivers prefer a larger safe distance. Meanwhile, as shown in figure 7.20, the aggressive model shows a greater proportion of large throttle movements (15.3% more than defensive when throttle > 50%), while the defensive model is more distributed in small throttle scale (73.6% when throttle < 50%). This phenomenon indicates that the aggressive model has a higher tendency of harsh acceleration, and the defensive model is milder on vehicle manoeuvre. Therefore, it can be noted from both findings that the tuning performance of ANFIS was satisfying.

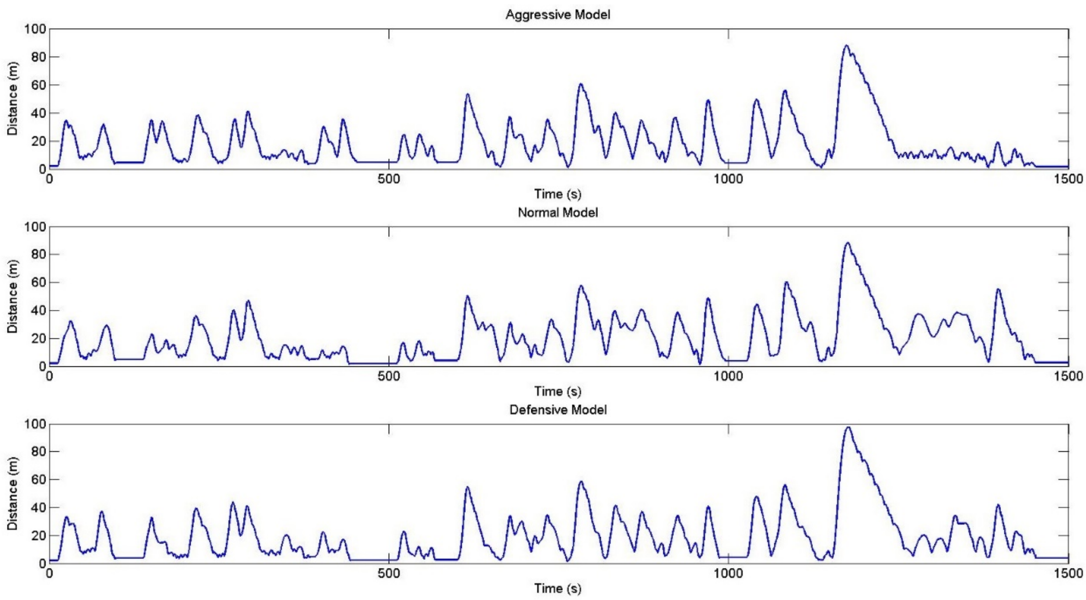


Figure 7.19. Headway distance profile of three models

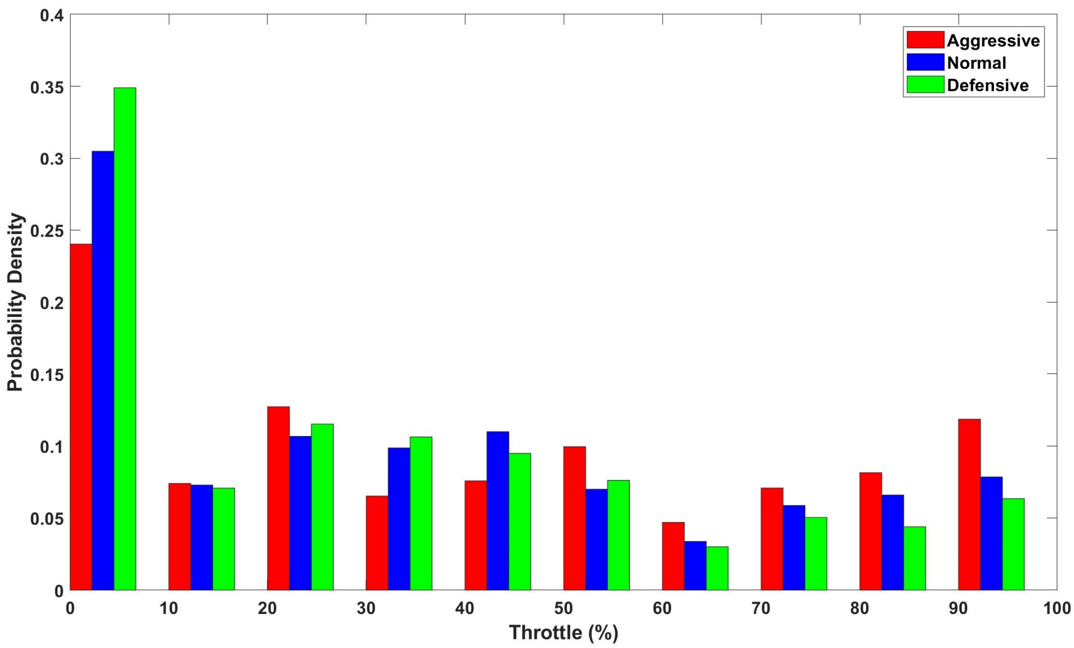


Figure 7.20. Throttle pedal distribution of three models

7.3 Model comparison and further evaluation

7.3.1 Modelling approach comparison

While both calibration approaches have been separately evaluated using the proposed simulation scenario, they are further compared in this section to determine which approach can achieve better performance in humanized modelling with the collected real driving data. Therefore, the distributions of throttle pedal position and time gap were computed and illustrated in figure 7.21 and figure 7.22.

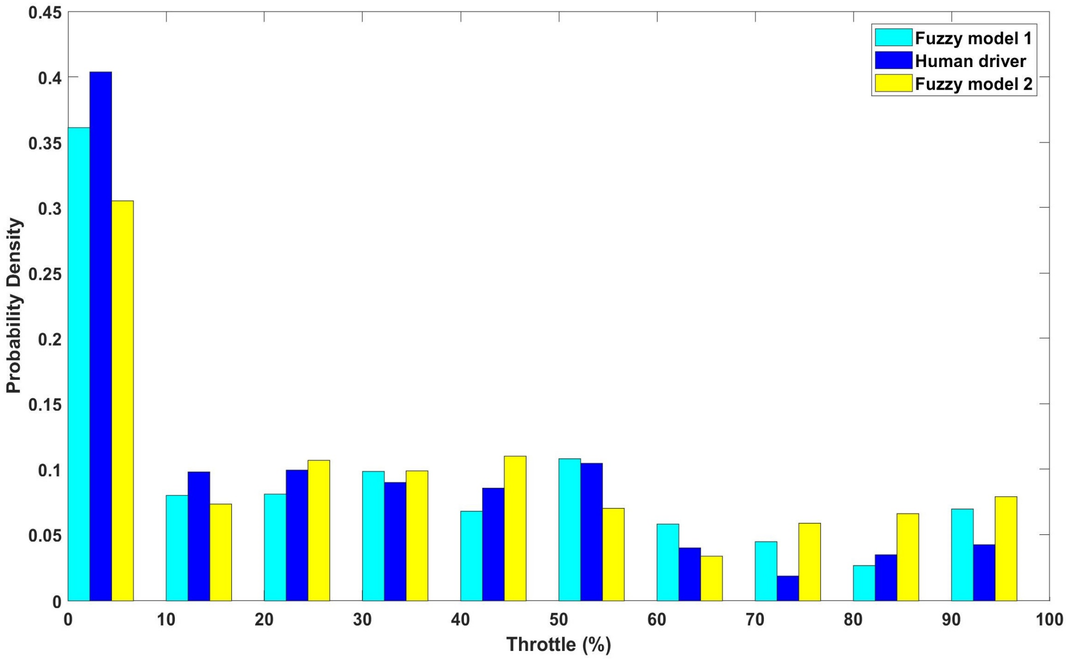


Figure 7.21. Throttle comparison between human and fuzzy models

As shown in figure 7.21, the difference between the two fuzzy models is not prominent. Neither of them can perfectly match the throttle distribution of the corresponding human driver. The human driver shows a higher distribution (39.7%) in throttle less than 10%, and a smaller distribution (13.4%) in throttle larger than 60%. This phenomenon can be easily interpreted. It is because the data of the human driver were collected during daily driving. Unlike the WLTC drive cycle, which contains several rapid accelerating scenarios, the movements of the leading vehicle in real life tend to be more gentle and predictable. Therefore, harsh acceleration can be more rare than following WLTC in the simulation. Moreover, slow-moving traffic flow is quite common in daily driving, especially when considering the data collection was mainly implemented during peak time. Thus, this phenomenon might be the reason of higher probability distributed in small throttle positions of the human driver. Nonetheless, a high correlation can be found between both fuzzy models and the human driver, as the largest probability difference is about 7.4%, which occurs in range (0 – 10%) between the second fuzzy model and the human driver.

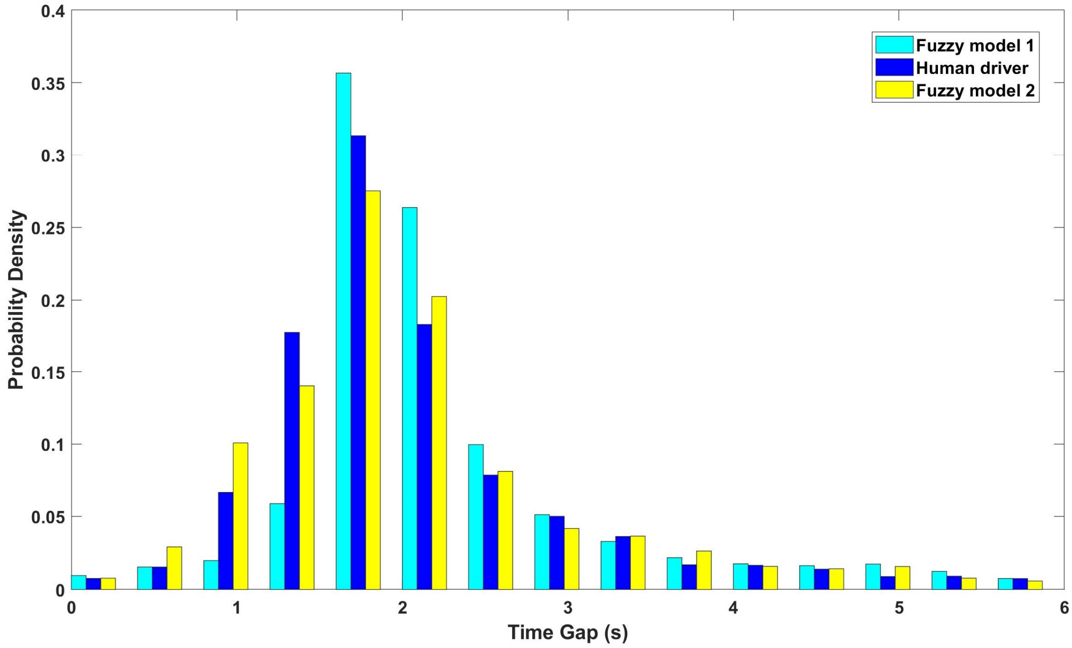


Figure 7.22. Time gap comparison between human and fuzzy models

Meanwhile, it can be noted from figure 7.22 that the distributed probabilities are very similar in time gap ranges smaller than 0.8s or larger than 2.8s. Moreover, the second fuzzy model tends to be more similar to the human driver in the middle range (0.8 – 2.8s). The accumulated absolute error is about 13.2% for the second fuzzy model in this range, 17.8% smaller than the first fuzzy model. Therefore, it can be noted that the second fuzzy model outperforms the first fuzzy model in replicating time gap behaviour of the human driver.

While the difference between both fuzzy models is not prominent, it should be noted that their performance in replicating human driving behaviours is promising, especially when comparing with the traditional PID-based driver model. Meanwhile, although the second fuzzy model performs better than the first fuzzy model in replicating time gap behaviour, it should be noted that some other factors should also be considered to evaluate these two modelling approaches. For instance, while the second fuzzy model can achieve better performance, its incorporated neural network demands a more complete dataset and is more time-consuming during training. Moreover, the local minimum can also restrict the training performance. Meanwhile, the first fuzzy model is easier to develop and tends to be more robust to incomplete data, but its performance can be affected by the suitability of expert knowledge. Therefore, it is difficult to determine which approach is the best overall option for humanized driver modelling. The first modelling approach is more suitable when accurate expert knowledge is obtained from the corresponding human driver, or the collected driving data is very limited. Meanwhile, the second approach is more preferred with a large complete set of real driving data, and has sufficient time for training. Nonetheless, either approach can achieve better performance than traditional PID models in replicating humanized driving behaviours.

Along with the comparison between the adopted driver modelling approaches, the correlations between driving style and fuel consumption were further investigated to improve the practical significance of this study. These two sets of calibrated models were evaluated separately.

7.3.2 Fuel consumption of driver model I

The fuel consumption distributions of three driving styles are illustrated in figure 7.23. It can be noted that the defensive model has the largest distribution in low fuel consumption range, about 60.4% for fuel consumption up to 3 litres/h. Meanwhile, the distributions of aggressive and normal models are quite similar within the same range, approximately 48.6% for both models. Fuel consumption of the normal model is more distributed in the middle range (3 – 6 litres/h), which occupies about 2% more than the aggressive model, and 10% more than the defensive model. Meanwhile, the aggressive model has larger probability distributed in fuel consumption more than 6 litres/h. It can be noted that the aggressive model occupies a larger proportion in the high fuel consumption segment, and the defensive model is more distributed in the low fuel consumption segment. This indicates that the aggressive driving style has a higher tendency to consume more fuel than the defensive driving style, which can be caused by some behaviours, such as harsh acceleration and deceleration, and abrupt speed change. Moreover, although exhaust emission is not directly simulated with the vehicle model, its changing tendency can still be estimated from the positive correlation between exhaust emission and fuel consumption (Fontaras et al., 2017). Therefore, it can be noted that a higher level of aggressivity tends to produce more exhaust emissions. Nonetheless, it should be noted that while the general tendency of fuel consumption distribution validates the hypothesis that aggressive driver consumes the most fuel and defensive driver consumes least, this trend is not consistent within some ranges. For example, in the range (3 – 4 litres/h), the distributed probability of the normal model is 3% larger than the aggressive model, and 7% larger than the defensive model.

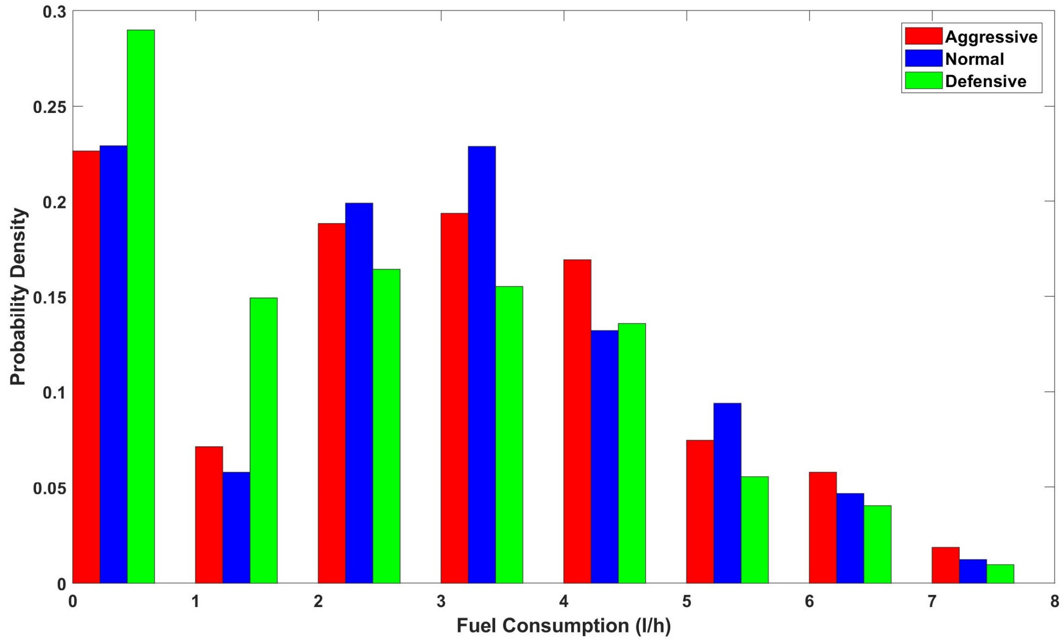


Figure 7.23. Fuel consumption of three driver models

The accumulated fuel consumption of three models was also estimated. As shown in figure 7.24, the difference between the established driving style models in the low speed segment is not prominent. This could be caused by the relatively small following distance, as aggressive driving is restricted in this scenario. Meanwhile, the variations of fuel consumption become more significant in the medium and high speed segments, revealing the potential influence of driving style on fuel consumption. The estimated total fuel consumption of the aggressive driver model was about 1.16 litre, which was approximately 6% more when comparing with the defensive driver model.

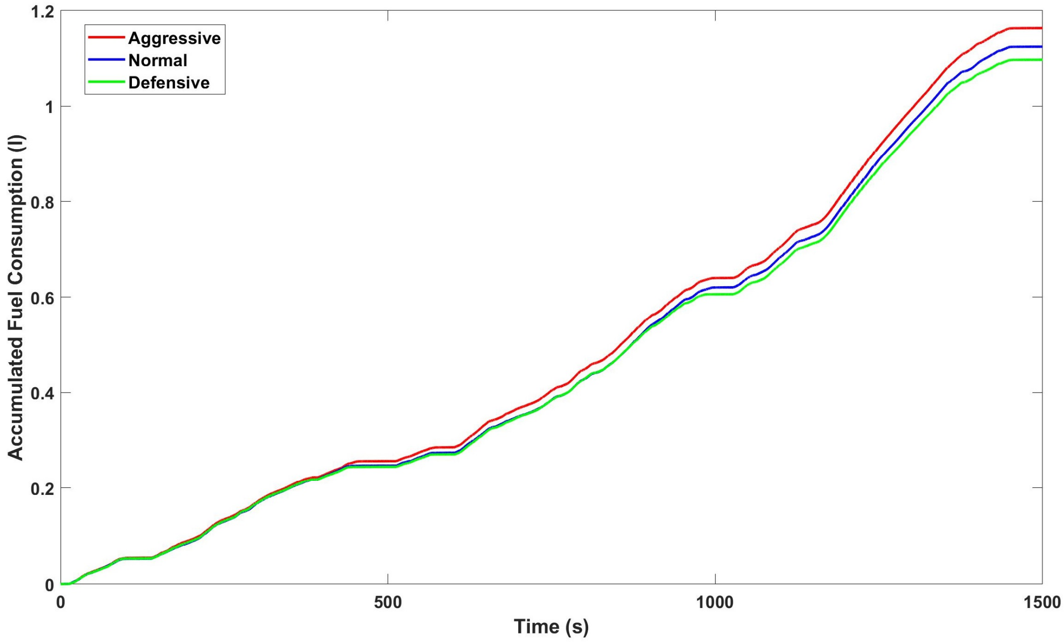


Figure 7.24. Accumulated fuel consumption of three driver models

7.3.3 Fuel consumption of driver model II

Along with the investigations into fuel consumption of the first set of driver models, the fuel consumption of the three driving style models calibrated using the second approach was also evaluated. The probability density distributions of fuel consumption were computed to demonstrate its variations between different driving styles. As illustrated in figure 7.25, it can be noted that the aggressive driver shows a larger possibility of high fuel consumption manoeuvres than the other models, especially for driving events that consumed more than 6 litres/h (6.3%). Meanwhile, the defensive driver occupies the largest proportion (63.4%) in the low fuel consumption range (0 - 3 litres/h). While the differences between fuel consumption were not significant, it can still be noted that the aggressive model tends to have more high fuel consumption manoeuvres, while the defensive model has fewer.

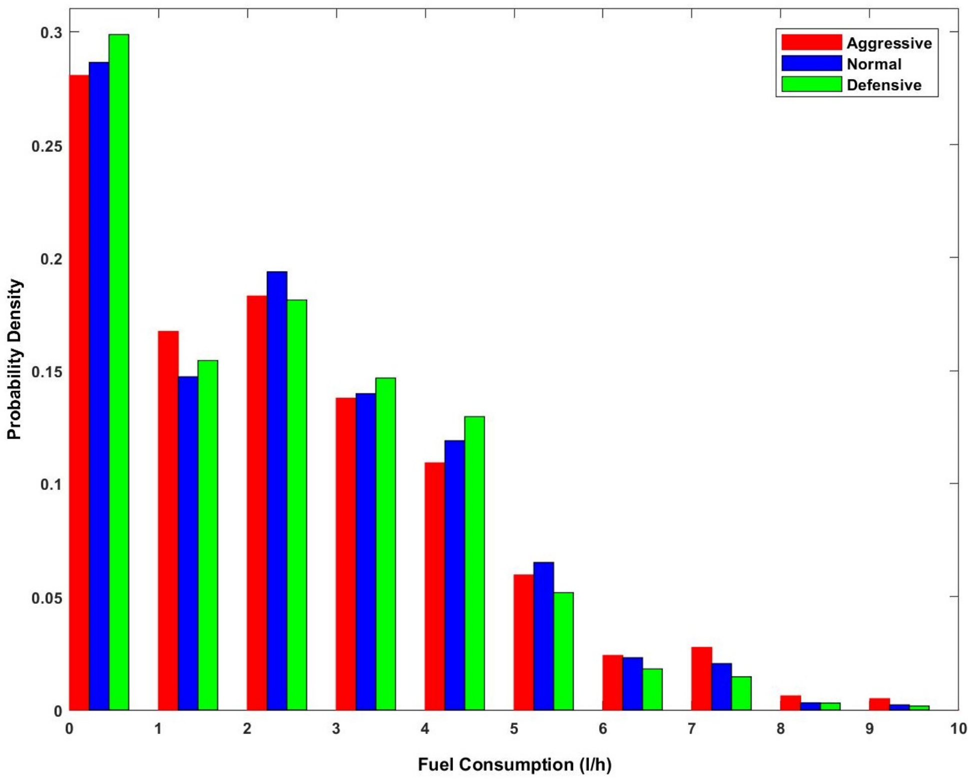


Figure 7.25. Fuel consumption distribution of three models

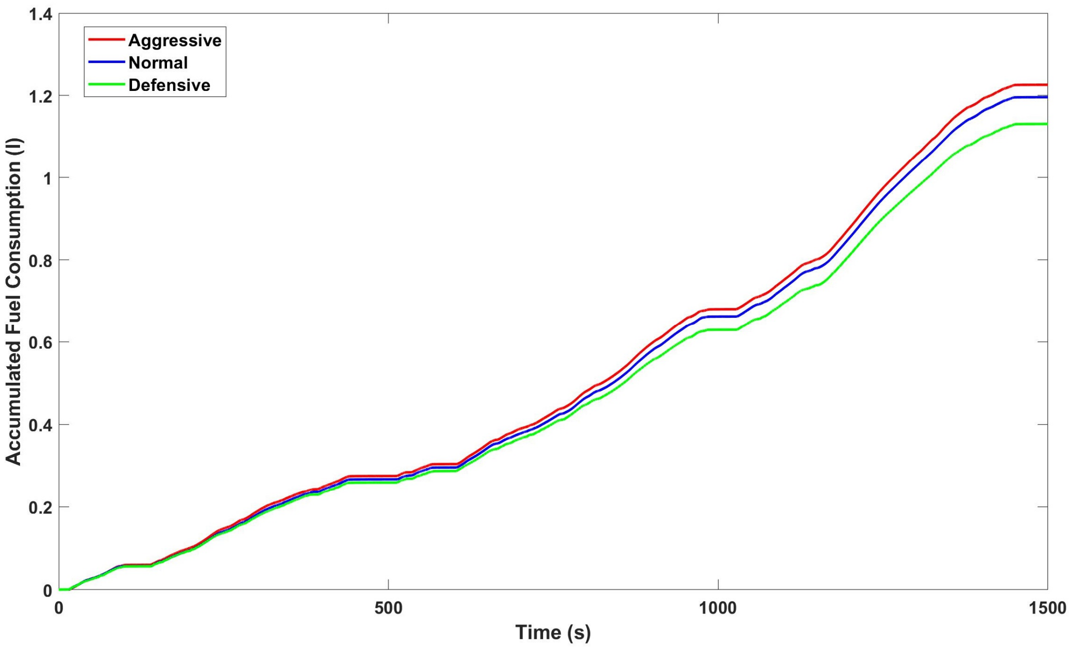


Figure 7.26. Accumulated fuel consumption of three driver models

The accumulated fuel consumption was also computed for this set of driver models. The obtained results are illustrated in figure 7.26. A similar trend can be noted that the difference of fuel consumption only becomes significant in the medium and high speed segments. The estimated total fuel consumption of each driver models was approximately 1.22 litre, 1.19 litre, and 1.13 litre, respectively. Therefore, it can be noted that the fuel reduction between the aggressive and defensive driver model was about 8%.

7.4 Chapter summary and conclusions

This chapter presents the results of vehicle modelling, gear shifting point clustering, and simulation evaluation of the driver models calibrated using two different approaches.

It can be noted that the primary aim of investigating the influence of driving style on fuel consumption through developing personalised driver models was basically achieved. A vehicle model representing the instrumented vehicle was first developed to facilitate the investigation. The performance and accuracy of this vehicle model was validated using WLTC drive cycle data collected during chassis dynamometer experiments. Afterwards, both sets of driver models were connected to this vehicle model and evaluated using the proposed simulation scenario anchored to the standard WLTC test. The throttle pedal position and time gap were selected as feature parameters to examine the similarity between the established driver model and the corresponding human driver. A PID-based driver model was also developed to facilitate the evaluation of the humanized feature of the fuzzy logic driver models. With satisfying results obtained, driver models representing different driving styles were hence developed. Throttle pedal position and headway distance were used to compare the difference among the established driver models. It was found that the aggressive driver model shows a higher tendency of tailgating and harsh acceleration, while the defensive driver model possesses the opposite trend.

Afterwards, two sets of driver models were also compared to evaluate the performance of the two calibration approaches. While both approaches show a satisfying performance in capturing human driving features, it was found that the second approach prevails in replicating time gap behaviour. However, neither of these two approaches is the best overall option, as they have corresponding advantages and drawbacks. The first approach tends to be more efficient and robust to incomplete data, but demands accurate expert knowledge to design the fuzzy controller. Meanwhile, the second approach is more intelligent and can perform better, but tends to be more time-consuming and relies on the completeness of collected data. Nonetheless, both approaches prevail the traditional PID-based driver models in replicating humanized driving behaviours.

Finally, the fuel consumption of both sets of driver models was investigated to evaluate the influence of different driving styles. It was found that the aggressive models tend to have more high fuel consumption manoeuvres, while the defensive models have fewer. Meanwhile, the accumulated fuel consumption was also computed for both sets of driver models. During the proposed simulation scenario, the first set of aggressive model can consume up to 6% more fuel than the defensive model, while the fuel reduction can be 8% for the second set of driver models.

Chapter 8 – *Conclusion and further work*

This final chapter summarises the conclusions, contributions and impacts of the work presented in this thesis. Meanwhile, some suggestions and recommendations for future study in this area are also presented.

8.1 Summary, contributions and impacts

In this thesis, the investigation on the influence of different driving styles on fuel consumption through personalised driver modelling has been presented. In accordance with the eight primary objectives laid out in Chapter 1, the achievements in this study will be discussed specifically.

- *Review the existing literature on driving style and its correlation with fuel consumption.*

In order to evaluate the potential influence of driving style on fuel consumption, a novel literature review was conducted to review the existing studies on various technology aids to promote eco-driving. The definition and classification of driving style were discussed first. While there has been no consensus on a unified definition of this concept, ten different definitions located in relevant studies were compared, and similar underlying essences among them were found. Therefore, a more generalised definition of driving style was proposed to facilitate the location of relevant studies. Meanwhile, the classified driving style groups in fifteen studies were also discussed, with five specific types (aggressive, normal, eco-driving, inattention, and defensive) described in detail. Afterwards, technology aids to promote eco-driving were also reviewed, ranging from conducting training programs to developing in-vehicle assistance tools. While training programs can easily reach more end-users, the deteriorating long-term effect and the potential cost are major concerns for this type of eco-driving promotion approach. Meanwhile, the in-vehicle assistance tools are more cost-effective solutions. However, fuel reductions with these devices are usually less evident than training programs, which could be caused by the deficiency in data acquisition approach and driving style optimisation algorithms. Nonetheless, the positive correlation between improved driving style and fuel consumption has been confirmed through the review of these existing studies.

- *Review various approaches of driver modelling and associated feature parameter selection.*

Meanwhile, another novel literature review was conducted aiming to evaluate the existing studies on driver modelling that addressed human factors. The approach of systematic literature review was adopted to organise the process of locating relevant studies. The literature search was conducted in six electronic databases using three sets of predefined strings, resulting in a final selection of 48 published articles. Through a preliminary analysis of identified studies, a growing research interest in this emergent field was confirmed. Afterwards, the located studies were roughly divided into two major groups based on their underlying approaches, namely numerical and artificial intelligence. While numerical models prevail in the high computation efficiency, their performance in replicating human driving styles still needs more thorough evaluations. Meanwhile, artificial intelligence models are calibrated from the collected real driving data, which allows the incorporation of more humanized control parameters and can hence improve their similarity to human drivers. However, a major drawback of these models is the high computation complexity, which restricts their feasibility in macroscopic traffic simulations. Moreover, the selected feature parameters in these studies were also evaluated. While there has been no consensus on this selection, variables like host vehicle speed, relative speed between host and preceding vehicle and headway distance, are found to be the best option for car-following regimes. Meanwhile, steering angle, road curvature, and lateral position are commonly used when considering lateral movements. Moreover, pedal position is also identified as a prominent parameter when differentiating diver and vehicle as separate units.

- *Collect on road real driving data using an instrumented vehicle and perform post-processing to acquire demanded information.*

In order to facilitate humanized driver modelling, a VW Sharan was instrumented for real driving data collection. While vehicle information was directly retrieved from ECU through a data logger, traffic information was obtained using a dashcam and a long-range radar. The data collection phase lasted approximately three months, with three human participants. The accumulated data files occupied approximately 1.93 TB. With the collected real driving data, essential post-processing was performed to extract useful information and facilitate following studies. While the vehicle state information can be easily obtained from the ECU data using provided software, a radar data processing tool and a novel video processing algorithm were developed to retrieve the traffic information. The proposed video processing algorithm can detect the leading vehicle and lane markers in each frame. The detected lane markers are used to locate the vanishing point, and hence formulate the transformation matrix between the world coordinates and pixel coordinates according to IPM. The headway distance can hence be computed with the detected vehicle position and formulated transformation matrix. Afterwards, sensor fusion based on Kalman filter has been performed to fuse sensory data from radar and camera to generate optimised headway distance measurements. The performance of this proposed algorithms were evaluated using the collected data. The accuracies of both sensors were separately examined first. Meanwhile, the robustness of the video processing algorithm to light condition and vehicle type was also investigated. Afterwards, the optimising performance of the adopted Kalman filter was also evaluated. It was found that the proposed approach has a strong robustness to various scenarios, and the optimising performance of Kalman filter was satisfying. This optimised headway distance was synchronised with the vehicle state information to form the real driving dataset. It can be noted that the proposed post-processing approach can effectively extract demanded information from the collected raw data. Therefore, the collected real driving data were processed using this proposed approach to facilitate future applications.

- *Classify different driving style using the driving data.*

With the collected real driving dataset, a novel SVC-based driving style classification approach was hence developed to differentiate the driving style variations from the data. The proposed approach consists of three steps. Firstly, each trip data are segmented into four driving events following the predefined criteria. Afterwards, the feature parameters of each event segment are derived by performing PCA on the combination of statistical and spectral features. Finally, these feature parameters are fed into SVC for driving style classification. During the evaluation of this proposed approach, it was found that the driving style variations could be efficiently differentiated during each trip. A high correlation between classified driving styles and fuel consumption was also confirmed. Moreover, it was also found that some external factors, such as weather condition, time of the day and driver's eagerness, can cause variations in driving style. Nonetheless, classified driving style labels were adopted to facilitate driver modelling.

- *Build driver models to represent different driving styles.*

Two fuzzy logic calibration approaches were adopted to infer the driver models from the classified real driving data for the first time. The first approach is based on K-means clustering and requires some expert knowledge, preferably from the corresponding drivers, to help define the basic structure of the fuzzy controller. Meanwhile, the second approach incorporates the training process of neural network to help infer the structure of the fuzzy controller. The developed neural network has a five-layer architecture with three inputs and one output. This neural network was adopted to infer the underlying relations between the driver's perceptron and control actions. Both approaches attempted to calibrate the driver models from the collected real driving data, which can improve the humanized feature of the obtained models. For each calibration approach, three driver models representing different relative driving styles (aggressive, normal and defensive) were developed. All these driver models were developed in Simulink to facilitate the easy incorporation with other software in future studies.

- *Verify the performance of the established driver models.*

In order to facilitate the verification of the established driver models, a Simulink-based vehicle model was hence developed. This vehicle model consists of five subsystems, which are engine, vehicle body, tires, brake, and transmission. The parameters of this vehicle model were tuned using the corresponding instrumented VW Sharan to minimize the potential basis introduced by this model. Moreover, the experimental data of the Sharan testing on chassis dynamometer were also adopted to evaluate the performance of the established vehicle model. With a satisfying evaluation result, the vehicle model was hence connected with the driver model for test purpose. Meanwhile, an anchored procedure to the standard WLTC drive cycle test was also created to set the simulation scenario. In the proposed procedure, the WLTC speed profile is assigned to a leading vehicle, and the host vehicle controlled by the driver model is required to follow it. This setting converts the change in speed profile to variations of headway distance. Therefore, the difference in cognition characteristics can also be incorporated, which can hence amplify the influence of different driving styles. The similarity between the established driver model and the corresponding human driver was evaluated through the comparisons of some identical parameters, such as headway distance, vehicle speed, and pedal position. It was found that the established fuzzy logic based driver model performs more similar to real human drivers, especially when comparing with a traditional PID-based driver model. Therefore, it can be noted that driver models developed using the proposed approach can be adopted to investigate the correlations between driving style and fuel consumption.

- *Investigate the correlations between driving styles and fuel consumption with the driver models.*

Following the developed approach of driver modelling, two more driver models representing different driving styles were calibrated. They were also connected to the vehicle model to investigate the variations of fuel consumption in the proposed simulation scenario. It was found that for the first set of driver models, the aggressive model could consume 6% more fuel than the defensive model, while the difference is about 8% for the second set of driver models.

- *Develop the process to calibrate personalised driver models.*

Along with the established and evaluated driver models, the process to develop personalised driver models was proposed in this thesis. It should be noted that the proposed process mainly consists of four steps, as illustrated in figure 8.1.

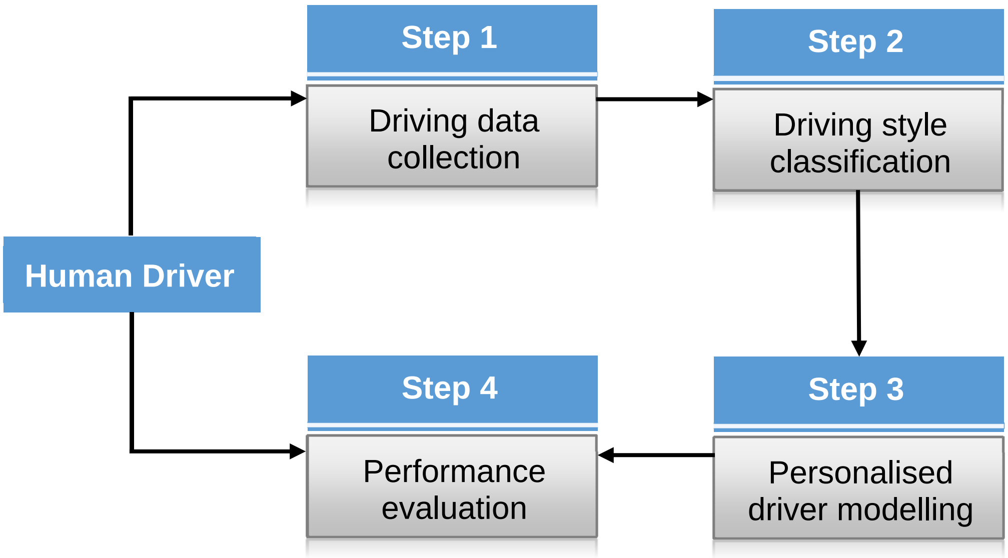


Figure 8.1. Proposed process to develop personalised driver models

As a data-driven modelling approach, the first step is to collect sufficient real driving data of the corresponding human driver through an instrumented vehicle. Afterwards, the driving style of the corresponding human driver should be differentiated using the proposed classification approach. In the third step, the personalised driver model can be developed using the proposed calibration approaches. Finally, the performance of the established driver model in mimicking the corresponding human driver can be evaluated using the proposed car-following simulation scenarios. Owing to the limitations during the data collection phase (e.g. limited number of participants and the availability of the instrumented vehicle), although only three driver models were established in this thesis, it should be noted that the developed process is capable of calibrating personalised driver models from their real driving data. This proposed process can be adopted to facilitate many related research areas. For instance, it can benefit the research on replicating the RDE tests on chassis dynamometer. Moreover, it can also be used to incorporate more personalisation and customization potentials to the development of ADAS and autonomous control strategy, which could be an important bonus feature to improve customers' acceptance on these technologies, as the vehicle can be driven in their own style.

8.2 Outlook

The work presented in this thesis can be considered as a preliminary investigation for future research in this area.

1. Two literature reviews have been conducted, focusing on promoting eco-driving and developing humanized driver models, respectively. In the first literature review, the effectiveness of existing approaches to promote eco-driving has been compared, with recommendations provided for future studies. Meanwhile, the modelling approaches and the adopted feature parameters are evaluated in the second review, to shed light on future research.

2. The vehicle instrumentation and data processing approach have provided an option for collecting headway distance information. It is expected that future study, especially for RDE test replication, will need this traffic-related information to reconstruct on-road driving scenarios.

3. The proposed SVC-based driving style classification approach can differentiate the driving style variations within each trip. Meanwhile, the influences of external factors, such as weather condition and the driver's eagerness, have also been investigated. These findings can benefit future studies to improve the integrity and performance of driving style classification.

4. The established personalised driver models can replicate three typical driving styles. They can be applied to other research that requires driver-in-the-loop. For example, they can be used to perform the direct control of robot drivers to introduce driving style variations to the standard drive cycle tests. Moreover, they can also be integrated in traffic simulations to evaluate the impact of different driving styles on traffic flow.

8.3 Further work

With the overarching aim of developing personalised driver models to investigate the influence of driving style on fuel consumption, this thesis has covered procedures ranging from data collection to simulation evaluation. Although the primary aims of this project are basically achieved, several potential further works have been identified during the study. These further works mainly consists of three aspects.

The first aspect is mainly associated with the data collection phase, as there have been several deficiencies identified. For example, owing to the lack of equipment, the information on road gradient and brake pedal force was not acquired. It should be noted that road gradient could affect the driver's decision on gear selection and pedal control behaviours. Meanwhile, brake pedal force can help to evaluate the driver's aggressiveness in braking scenarios. Therefore, it is recommended that both measurements should be collected in further works to improve the validity and robustness of the real driving dataset. Moreover, another further work identified for the data collection phase is the incorporation of more human participants. Although this thesis focuses on developing personalised models, collecting real driving data of more participants can help to improve the proposed driving style classification approach. A more robust and generic classification result can be obtained with more participants that possess different driving styles.

Along with further works for data collection, another potential further work is to integrate the established driver models with some existing software, such as IPG Carmaker and PTV Vissim. The vehicle dynamic models in Carmaker can be used to further evaluate the established driver models, and facilitate the investigations into potential variations caused by different vehicle types. Meanwhile, the established driver models can be assigned to different agents in the traffic simulation model of Vissim. Through this integration, it will be beneficial to investigate the influence of different driving styles on traffic flow, which can also amplify their impacts on fuel consumption. Both options can increase the significance of the established driver models, and hence further improve the contributions of this thesis.

Meanwhile, the third identified aspect of further works is to integrate the established driver models with a Stähle robot driver within PVRC. This robot driver has three legs for pedal control and an arm for gear shifting. In order to achieve the direct control of this robot driver, control commands in the extended AK protocol format need to be transmitted to the robot driver through socket communication. Some preliminary works have been completed to facilitate this integration.

As shown in figure 8.2, an interface GUI has been programmed using Python and QT. This GUI can be used to connect between the hosts of driver model, robot driver, and chassis dynamometer through socket communication. In the settings menu, typical specifications of the adopted vehicle can be predefined, such as maximum vehicle speed, maximum and minimum engine speed, gear shifting mode and shifting points. Meanwhile, the control mode of the robot driver can also be determined from three default options, which are pedal, speed, and engine mode. These parameters are used to define the conditions of safety precautions. Afterwards, during each update cycle, the vehicle state information can be transmitted from the robot driver to the driver model to generate the control demand, which will be converted into corresponding AK commands, and sent back to the robot driver. Meanwhile, the status of the vehicle and robot driver can also be live monitored in the GUI. Moreover, some safety precautions, such as emergency stop and sudden loss of connection, are also included in this GUI.

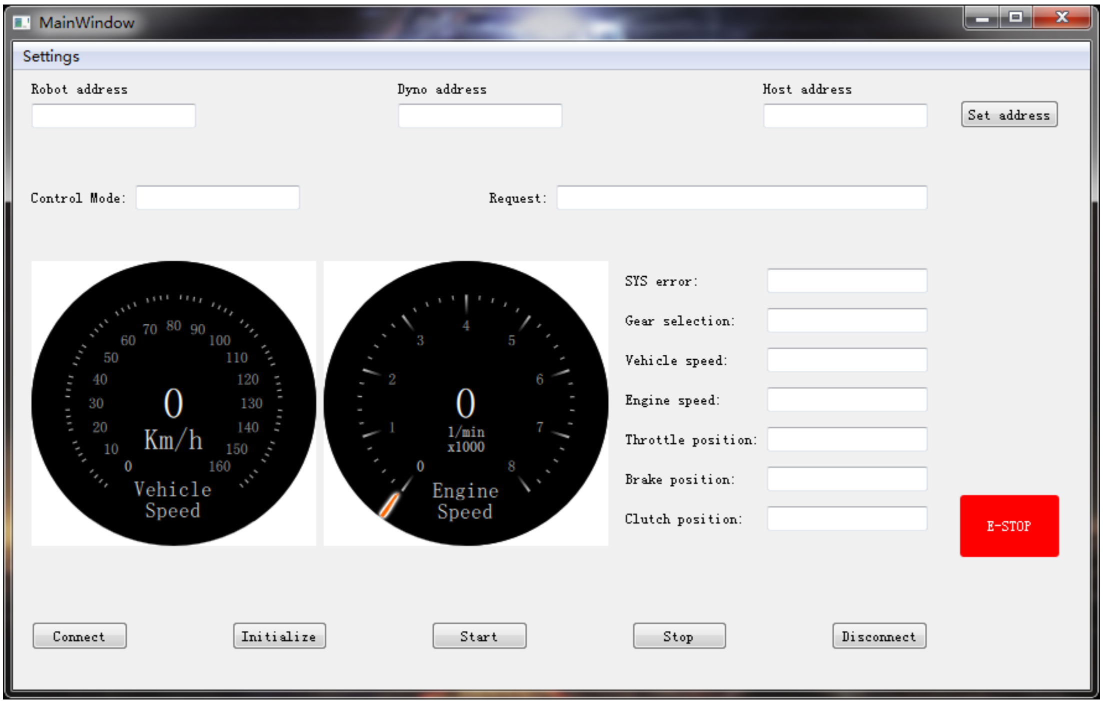


Figure 8.2. GUI for robot driver direct control

Some initial tests on the connection and information transmission have already been implemented to evaluate the performance and stability of this GUI, with satisfactory results obtained. Nonetheless, more extensive step-by-step evaluations are still needed to further evaluate its stability and extend its functionality, before it can be used to perform driver-in-the-loop experiments with the robot driver, an actual vehicle, and the chassis dynamometer.

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